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"Estimating Social Preferences and Kantian Morality in Strategic Interactions"

Boris Van Leeuwen and Ingela Alger

Toulouse School of Economics

Estimating Social Preferences and Kantian Morality in Strategic Interactions*

Boris van Leeuwen† Ingela Alger‡

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Abstract: Theory suggests that a form of Kantian morality has evolutionary foundations. To investigate the relative importance of Kantian morality and social preferences, we run a laboratory experiment on strategic interaction in social dilemmas. We structurally estimate social preferences and Kantian morality at the individual and aggregate level. We observe considerable heterogeneity in preferences. Finite mixture analyses show that the subject pool is well described as consisting of two or three types: all display a Kantian moral concern, which they combine with aheadness aversion, behindness aversion, or both. The value of adding Kantian morality to well-established preference classes is also evaluated.

JEL codes: C49, C72, C9, C91, D03, D84.

Keywords: social preferences, other-regarding preferences, Kantian morality, morality, experiment, structural estimation, finite mixture models.

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†Department of Economics, Tilburg University. b.vanleeuwen@uvt.nl

‡Toulouse School of Economics, CNRS, University of Toulouse Capitole, Toulouse, France, and Institute for Advanced Study in Toulouse. ingela.alger@tse-fr.eu

1 Introduction

Behavioral and experimental economics has over the past decades provided a host of insights about the motivations that drive human behavior in social dilemmas. Notwithstanding the wealth of preference classes that have been considered—notably, altruism (Becker, 1974), warm glow (Andreoni, 1990), inequity aversion (Fehr & Schmidt, 1999; Bolton & Ockenfels, 2000), reciprocity (Rabin, 1993; Charness & Rabin, 2002; Dufwenberg & Kirchsteiger, 2004; Falk & Fischbacher, 2006), guilt aversion (Charness & Dufwenberg, 2006; Battigalli & Dufwenberg, 2007), and image concerns (Bénabou & Tirole, 2006; Ellingsen & Johannesson, 2008)—recent theoretical work has shown that yet another type of preferences is strongly favored by evolutionary forces. The novel element is a form of Kantian moral concern, so called *Homo moralis* preferences (Alger & Weibull, 2013; Alger, Weibull, & Lehmann, 2020). The Kantian moral concern induces the individual to evaluate each course of action in the light of what material payoff (s)he would achieve, should others choose the same course of action. Theoretical analyses show that—compared to consequentialistic social (or selfish) concerns—this Kantian moral concern leads to qualitatively different behavioral predictions in many situations, such as consumption choices when these entail externalities (Laffont, 1975; Daube & Ulph, 2016), voting for environmental policies (Eichner & Pethig, 2021), voter coordination as well as information aggregation in large electorates (Alger & Laslier, 2022), incentive provision to teams (Sarkisian, 2017), voluntary contributions to public goods and willingness to pay taxes (Muñoz Sobrado, 2022), and standard finite normal-form games (Alger & Weibull, 2013; Bomze, Schachinger, & Weibull, 2021). The purpose of this paper is to examine the explanatory power of such Kantian moral concerns, when these are assumed to be at work alongside social preferences such as altruism and inequity aversion. We do this by way of conducting an experimental study.

The laboratory experiment consists in letting each subject choose strategies in three classes of two-player social dilemmas: sequential prisoners' dilemmas, mini trust games,

and mini ultimatum bargaining games. In such sequential games one subject moves before the other, and it is this feature that allows us to distinguish consequentialistic motives from Kantian morality (à la *Homo moralis*, Alger & Weibull, 2013). Indeed, since each subject is told that he stands an equal chance of being a first- and a second-mover, Kantian morality would make him attach some value to the material payoff he would obtain if he played against himself. By contrast, a subject with purely consequentialistic preferences would make the subject attach value solely to the material payoff distribution that he expects to realize, given his beliefs about the opponent's strategy.[1]

In the main, pre-registered, analysis we posit a utility function with three parameters capturing attitudes towards unfavorable inequity, favorable inequity, and the Kantian moral concern, and we use the observed individual choices and reported beliefs in 18 different games (six games in each game class) to structurally estimate the preference parameter values for each individual subject, using a standard random utility model.[2] The use of such structural models has become more commonplace in experimental and behavioral economics, including the estimation of social preferences (DellaVigna, 2018). We also perform aggregate estimations, using a finite mixture approach, the same as that used by Bruhin, Fehr, and Schunk (2019) in their statistical analysis of social preferences.[3] We conduct estimations under two assumptions about attitudes towards risk (risk neutrality and risk aversion). While the analysis that yields the best fit allows for risk aversion, we first present the results assuming risk neutrality, for ease of comparability with

[1] It is well known that the ability to control for subjects' beliefs when trying to identify their preferences is important (Bellemare et al., 2008; Miettinen et al., 2020). This is particularly true here, for Kantian morality reduces the sensitivity to beliefs. In the extreme case of an individual who would be driven entirely by the Kantian moral concern, the beliefs about the opponent's strategy would indeed be irrelevant, for such an individual would simply choose the "right thing to do." Hence, information about subjects' beliefs is crucial to distinguish Kantian moral concerns from consequentialistic ones. Accordingly, instead of hypothesizing subjects' beliefs about the behavior of their opponents (for example by some equilibrium hypothesis), we elicit each subject's belief in each strategic interaction. In further robustness checks, we also impose rational expectations instead.

[2] Social image concerns (Bénabou & Tirole, 2006) are muted because subjects are anonymously and randomly matched.

[3] See also Bardsley and Moffatt (2007), Iriberri and Rey-Biel (2013) and Breitmoser (2013), who use related mixture models to capture heterogeneity in social preferences.

other studies. The results are qualitatively similar, except for the attitude towards favorable inequity.

The estimations at the level of the individual subjects reveal substantial heterogeneity in preferences. While many subjects appear to be averse to unfavorable inequity (behindness aversion) and favorable equity (aheadness aversion), some appear to be either indifferent or like favorable inequity. Importantly, the behavior of most subjects is compatible with some concern for Kantian morality. Kantian morality further appears in all the aggregate estimations. The representative agent in the subject pool combines inequity aversion with Kantian morality. Models with two or three types provide a much better fit than the representative agent model. Our finite mixture estimations thus capture the heterogeneity in a tractable way. The two-types model has one type that combines inequity aversion with Kantian morality, while the other type combines behindness aversion with Kantian morality. With three types, all types display a concern for Kantan morality, combined with either behindness aversion, aheadness aversion, or a combination of the two (i.e. inequity aversion). Importantly, allowing for Kantian morality substantially improves the fit of the model. We compare models allowing for combinations of distributional social preferences (e.g. inequity aversion or altruism), Kantian morality, and negative reciprocity as in Charness and Rabin (2002). At the aggregate level, allowing for Kantian morality substantially improves the fit of the finite mixture models, and more so than allowing for reciprocity does.

When allowing for risk aversion, the fit of our models substantially improves compared to assuming risk neutrality. As under risk neutrality, the finite mixture models capture the heterogeneity in a tractable way. With two or three types, we again observe that all types display a concern for Kantian morality, often combined with "behindness aversion", but in contrast to the risk neutral case we now observe stronger heterogeneity in the attitude towards favorable inequity. Under risk aversion the two-types model has one type that combines (mild) inequity aversion with Kantian morality, while the other

type combines "spite" or "competitiveness" – an aversion to being behind and taste for being ahead – with Kantian morality. While the prevalence of spite may appear surprising, it is in line with the theoretical prediction of Alger et al. (2020), who show in a general model that preferences that combine material self-interest, a Kantian moral concern and a social concern at the material payoff level is what should be expected in most human populations. With such preferences, pro-social behavior appears as long as the Kantian moral concern is strong enough to outweigh the spite. As noted above, the spiteful type does not appear under risk neutrality, however.

Our paper fits in the large literature that estimates or tests models of social preferences.[4] In relation to this literature, our main contribution is that we allow for the possibility of Kantian morality as part of the motivation behind subjects' choices, in addition to social preferences. Closest to our work is the paper by Miettinen et al. (2020), who also allow for this possibility.[5] Our study is similar to theirs in two respects. First, both experiments rely on sequential games (our experimental design was indeed inspired by theirs in this respect). Second, in both experiments the subjects' beliefs about opponents' choices are elicited and used as controls in the empirical estimations. The key difference between ours and their study is that our data set is much richer: we collect data on individual choices in 18 strategic interactions while in their study each subject faces one single sequential prisoners' dilemma. Our data set gives us access to a rich set of empirical tools. In particular, while Miettinen et al. (2020) compare the explanatory power of six alternative utility functions, which involve either a consequentialistic, a reciprocity,

[4]See, for example, Palfrey and Prisbrey (1997); Andreoni and Miller (2002); Charness and Rabin (2002); Engelmann and Strobel (2004); Bardsley and Moffatt (2007); Fisman, Kariv, and Markovits (2007); Bellemare et al. (2008); Blanco, Engelmann, and Normann (2011); DellaVigna, List, and Malmendier (2012); Breitmoser (2013); Iriberri and Rey-Biel (2013); Ottoni-Wilhelm, Vesterlund, and Xie (2017) and, for recent surveys, see Cooper and Kagel (2015) and Nunnari and Pozzi (2022). Closest to our work in terms of empirical strategy is the recent study by Bruhin et al. (2019), who use the same finite mixture approach as we do, but who do not consider Kantian morality.

[5]See also Capraro and Rand (2018), who evaluate the explanatory power of *Homo moralis* preferences in standard games; however, and by contrast to our experiment and that by Miettinen et al. (2020), they rely on framing. More generally, economists are increasingly seeking to evaluate the explanatory power of non-consequentialistic motives; see, e.g., Bénabou, Falk, Henkel, and Tirole (2020).

or a Kantian concern, our data set enables us to estimate preference parameters at the individual level, and to apply finite mixture methods in order to detect the presence of common preference types that *combine* social preferences and Kantian morality. As indicated by our results, most subjects indeed appear to have such complex preferences. Furthermore, our data allows us to conduct out-of-sample predictions to evaluate the explanatory power of the estimated preference types.

The remainder of this paper is organized as follows. Section 2 describes the experimental design and introduces the class of preferences we estimate, and Section 3 presents our econometric approach. The results of the pre-registered analysis (no reciprocity, subjective beliefs, and risk neutrality) are presented in Section 4, and we check the robustness of these results to allowing for risk aversion and rational expectations in Section 5. In Section 6 we incorporate reciprocity, and we also report several measures of the value added of Kantian morality in our experiment. Section 7 concludes.

2 The experiment: game protocols, preferences, and procedures

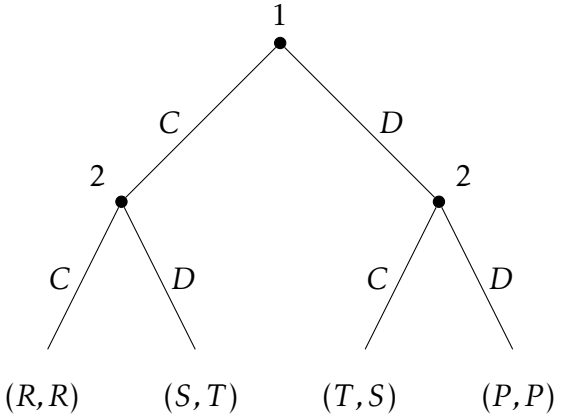
2.1 Game protocols

In the experiment, subjects play three types of well-known game protocols, illustrated in Figure 1: the Sequential Prisoner's Dilemma protocol (SPD), shown in Figure 1a, the mini Trust Game protocol (TG), shown in Figure 1b, and the mini Ultimatum Game protocol (UG), shown in Figure 1c.[6] We use the standard notation for prisoners' dilemmas, where R stands for "reward", S for "sucker's payoff", T for "temptation", and P for "punishment", and we throughout assume $T > R > P > S$.

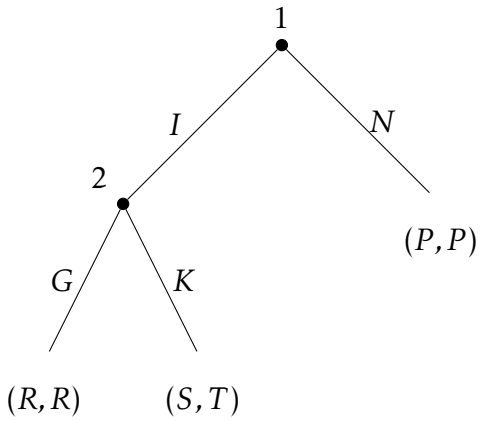
The objective of the experiment is to test whether Kantian morality (à la *Homo moralis*,

[6] By a "game protocol", we mean a game tree and associated monetary payoffs.

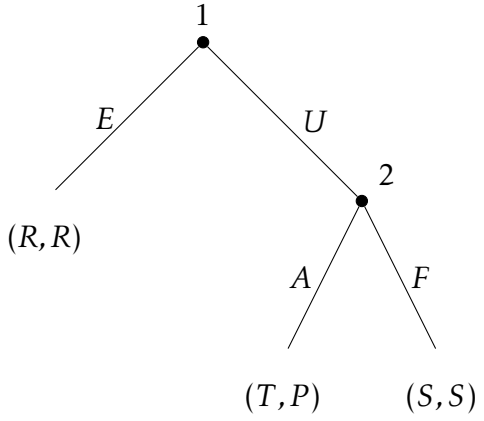
Figure 1: Game protocols



(a) Sequential Prisoner's Dilemma game protocol

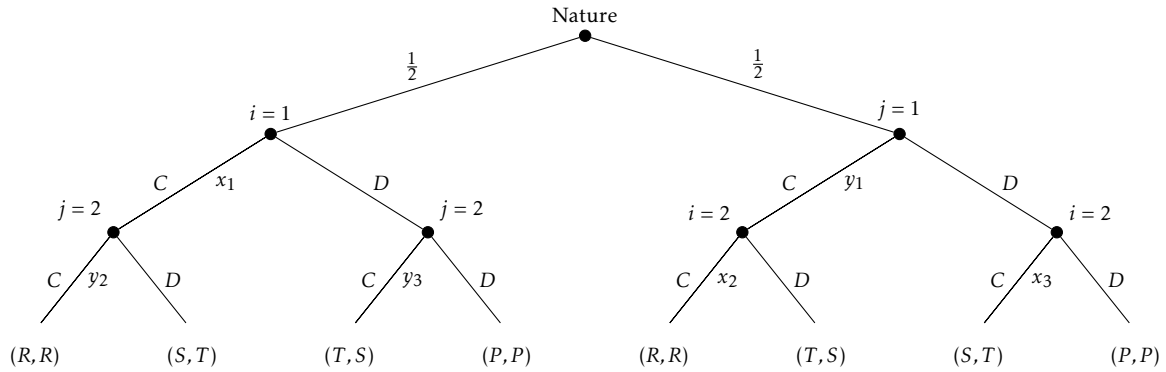


(b) Trust Game protocol



(c) Ultimatum Game protocol

Figure 2: Meta-game protocol for the SPD



Alger & Weibull, 2013) can help explain the choices subjects make in these game protocols. A subject with such Kantian morality evaluates each strategy in the light of what his/her material payoff would be if, hypothetically, the opponent were to choose the same strategy. This requires that the interaction is symmetric. To symmetrize the game protocols in Figure 1—which are asymmetric with one first-mover and one second-mover—we make it clear to the subjects that they are equally likely to be drawn to play in each player role. This defines a symmetric (meta) game protocol, in which "nature" first draws the role assignment, with equal probability for both assignments, and then the players learn their respective roles. The game tree corresponding to this game protocol for the SPD is shown in Figure 2. A behavior strategy consists of specifying (potentially randomized) choices at *all* decision nodes in this game protocol. Let $x = (x_1, x_2, x_3)$ denote the behavior strategy of subject i in this game tree: x_1 is the probability that i plays C as a first mover, x_2 the probability that i plays C as a second mover following play C by the opponent, and x_3 the probability that i plays C as a second mover following play D by the opponent. Likewise, let $y = (y_1, y_2, y_3)$ denote the behavior strategy used by the opponent (subject j). Each strategy pair (x, y) determines the realization probability $\eta_{(x,y)}(\gamma)$ of each play γ of the game protocol, where a *play* is a sequence of moves through the game tree, from its "root" to one of its end nodes (see Figure 2). For example: $\eta_{(x,y)}((1, C, C)) = \frac{x_1 \cdot y_2}{2}$ and

$\eta_{(x,y)}((2,D,C)) = \frac{(1-y_1)\cdot x_3}{2}$.

Turning to the two other game protocols, when the trust game protocol is symmetrically randomized, a behavior strategy is a vector, $x = (x_1, x_2) \in [0,1]^2$, where x_1 is the probability with which i invests (selects I) and x_2 the probability with which i gives back something (selects G) if the first-mover invested. When the ultimatum game protocol is symmetrically randomized, a behavior strategy is a vector, $x = (x_1, x_2) \in [0,1]^2$, where x_1 is the probability with which i proposes an equal sharing (selects E), and x_2 the probability with which i accepts an unequal sharing (selects A). Like in the SPD game protocol, for both the TG and the UG protocols we denote by $y = (y_1, y_2)$ the strategy of i's opponent j, and write $\eta_{(x,y)}(\gamma)$ to denote the probability of each play γ of the game protocol at hand.

Having formally defined the game protocols, we are in a position to define the utility function that we posit.

2.2 Preferences

In our empirical analysis we posit preferences that combine material self-interest, attitudes towards being ahead as well as behind (Fehr & Schmidt, 1999), (negative) reciprocity (Charness & Rabin, 2002), and a Kantian moral concern (Alger & Weibull, 2013). Thus, let the expected utility of a subject i playing against a subject j be

$$\begin{aligned} u_i(x,y) \;=\; & (1-\kappa_i)\cdot\sum_{\gamma}\eta_{(x,y)}(\gamma)\cdot\pi_i(\gamma) \\ & -\alpha_i\cdot\sum_{\gamma}\eta_{(x,y)}(\gamma)\cdot\max\left\{0,\pi_j(\gamma)-\pi_i(\gamma)\right\} \\ & -\beta_i\cdot\sum_{\gamma}\eta_{(x,y)}(\gamma)\cdot\max\left\{0,\pi_i(\gamma)-\pi_j(\gamma)\right\} \\ & -\delta_i\cdot q\cdot\sum_{\gamma}\eta_{(x,y)}(\gamma)\cdot\left(\pi_j(\gamma)-\pi_i(\gamma)\right) \\ & +\kappa_i\cdot\sum_{\gamma}\eta_{(x,x)}(\gamma)\cdot\pi_i(\gamma), \end{aligned} \tag{1}$$

where x and y are i's and j's behavior strategy, respectively, $\pi_i(\gamma)$ is i's material payoff following play γ and $\pi_j(\gamma)$ that of j, and $q = 1$ if j 'misbehaved' and $q = 0$ otherwise.[7] We follow Charness and Rabin (2002) by labeling a first-mover action as misbehavior if it excludes an outcome that has maximal joint monetary payoffs.[8]

This utility function has four parameters. Two of them are the familiar measures of inequity aversion. The parameter α_i captures i's disutility (if $\alpha_i > 0$) or utility (if $\alpha_i < 0$) from disadvantageous inequity, i.e., from falling short in terms of material payoff in the interaction. Likewise, the parameter β_i captures i's disutility (if $\beta_i > 0$) or utility (if $\beta_i < 0$) from advantageous inequity, i.e., from being ahead in terms of material payoff. The third parameter, δ_i, is the reciprocity parameter. The fourth parameter, κ_i, captures a Kantian moral concern (à la *Homo moralis*, Alger & Weibull, 2013). It places weight on the expected material payoff that the subject would obtain if, hypothetically, both individuals were to use the subject's strategy x. Under this hypothesis, the probability that a play γ would occur is $\eta_{(x,x)}(\gamma)$. A κ_i-value strictly between zero and one represents a partly deontological motivation, an individual who, in addition to the social concern that consists in caring about his or her own material payoff and that to the other individual in the interaction, is also motivated by what is the "right thing to do", what strategy to use if it were also used by the opponent. To choose a strategy x in order to maximize the last term in (1) is to choose a strategy that maximizes material payoff if used by both subjects (see Alger & Weibull, 2013, for a discussion).[9]

The utility function in (1) nests many familiar utility functions in the literature. Clearly,

[7] Note that we assume "ex-post" inequity aversion. For a discussion of "ex-post" and "ex-ante" inequity aversion, see for example Krawczyk and Le Lec (2010), Cappelen, Konow, Sørensen, and Tungodden (2013), Brock, Lange, and Ozbay (2013) and Krawczyk and Le Lec (2016).

[8] For our case this means that defecting as a first mover in a SPD protocol (if $2R > T+S$), and not investing in a TG protocol constitutes misbehavior (note, however, that the δ_i term cancels in the latter case, as not investing will lead to equal payoffs for both players). In addition, we also label not proposing an equal split in the UGs as misbehavior.

[9] Note that the *Homo moralis* motivation is clearly distinct from behavioral motivations based on biased beliefs, such as the false consensus effect (Ross, Greene, & House, 1977) or magical thinking (Daley & Sadowski, 2017), whereby an individual overestimates the likelihood that the opponent plays the same strategy as him/her. Any such biased beliefs would indeed appear in the first term in the utility function in (1).

setting all four parameters to zero, $\alpha_i = \beta_i = \kappa_i = \delta_i = 0$, represents pure self-interest and thus amounts to the classical *Homo oeconomicus*. The Fehr and Schmidt (1999) model of inequity aversion is obtained by setting $\alpha_i \geq \beta_i > 0$ and $\kappa_i = \delta_i = 0$. One obtains Becker's (1974) model of pure altruism by setting $\kappa_i = \delta_i = 0$ and $\alpha_i = -\beta_i$, for some $\beta_i \in (0, 1/2]$.[10] Here β_i is the individual's "degree of altruism", the weight placed on the other subject's material payoff, while the weight $1 - \beta_i$ is placed on own material payoff. Pure *Homo moralis* preferences are obtained by setting $\alpha_i = \beta_i = \delta_i = 0$ and $\kappa_i \in (0, 1]$. Here κ_i is the individual's "degree of Kantian morality", the weight placed on the material payoff that would be obtained if both subjects in the interaction at hand played x, the strategy used by individual i, while the weight $1-\kappa_i$ is placed on own material payoff, given the strategy profile (x, y) effectively played. Finally, the utility function in (1) also nests the Charness and Rabin (2002) model with negative reciprocity when δ_i, α_i, and β_i are non-nil and $\kappa_i = 0$. Note that the reciprocity parameter δ_i is akin to a modification of the behindness aversion parameter α_i following misbehavior by the first mover.

2.3 Experimental procedures

In total, 136 subjects (69 men, 67 women) participated in the experiment. We conducted 8 sessions at the CentERlab of Tilburg University, with between 12 and 22 subjects per session. Using the strategy method, each subject made decisions both as a first mover and a second mover for 18 game protocols (6 SPDs, 6 TGs and 6 UGs),[11] for different monetary payoff assignments T, R, P and S, listed in Table 1.[12]

All payoffs are denoted in 'points', where one point is equivalent to 17 eurocents. At

[10] See also the note by Engelmann (2012) on extending inequity aversion models to incorporate altruism.

[11] Iriberri and Rey-Biel (2011) find that "role uncertainty" increases social welfare maximizing behavior and decreases self-interested behavior in dictator games. Note that to estimate Kantian morality concerns, we require symmetric games and hence need a form of role uncertainty in our design (see subsection 2.1). Possibly, this means that with our design we estimate an upper bound on the importance of social preferences.

[12] In the process of selecting the number of game protocols and the monetary payoffs, we conducted simulations to verify if we could retrieve the simulated parameters, see also Appendix A5 for examples of these simulations.

Table 1: Game protocols: monetary payoffs, actions and beliefs

No.	T	R	P	S	x_1	x_2	x_3	y_1	y_2	y_3
Sequential Prisoner's Dilemmas										
1	90	45	15	10	0.18	0.15	0.10	0.33	0.20	0.13
2	90	55	20	10	0.24	0.20	0.06	0.30	0.21	0.07
3	80	65	25	20	0.35	0.29	0.13	0.32	0.30	0.16
4	90	65	25	10	0.29	0.31	0.03	0.31	0.25	0.08
5	80	75	30	20	0.43	0.50	0.04	0.40	0.41	0.11
6	90	75	30	10	0.30	0.40	0.01	0.33	0.33	0.08
All SPDs					0.30	0.31	0.06	0.33	0.28	0.11
Trust Games										
7	80	50	30	20	0.44	0.27	.	0.41	0.23	.
8	90	50	30	10	0.18	0.18	.	0.33	0.19	.
9	80	60	30	20	0.56	0.35	.	0.47	0.30	.
10	90	60	30	10	0.35	0.25	.	0.37	0.24	.
11	80	70	30	20	0.62	0.51	.	0.54	0.42	.
12	90	70	30	10	0.46	0.40	.	0.42	0.31	.
All TGs					0.44	0.33	.	0.42	0.28	.
Ultimatum Games										
13	60	50	40	10	0.49	0.96	.	0.48	0.91	.
14	65	50	35	10	0.52	0.96	.	0.49	0.88	.
15	70	50	30	10	0.46	0.96	.	0.47	0.87	.
16	75	50	25	10	0.43	0.90	.	0.47	0.83	.
17	80	50	20	10	0.60	0.88	.	0.51	0.79	.
18	85	50	15	10	0.60	0.81	.	0.55	0.72	.
All UGs					0.51	0.91	.	0.50	0.83	.

Notes: Here x_1, x_2 and x_3 denote action frequencies. In the SPDs, x_1 is the frequency by which the first mover plays C, x_2 the frequency by which the second mover plays C after C, and x_3 the frequency by which she plays C after D. In the TGs, x_1 is the frequency by which the first mover plays I, and x_2 the frequency by which the second mover plays G after I. For the UGs, x_1 is the frequency by which the first mover plays E, and x_2 the frequency by which the second mover plays A after U. Likewise, y_1, y_2 and y_3 are the mean values of the stated beliefs about x_1, x_2 and x_3. Table based on all 136 subjects.

the beginning of each session, the order of the 18 game protocols was fully randomized, meaning that participants could for example play an UG protocol first, then a TG protocol, followed by an SPD, and then another TG. For each game protocol, subjects first indicated what they would do at each decision node and second what they believed others would do at each decision node.[13] In all game protocols, we used neutral labels. Two of the 18 game protocols were randomly selected for payment. To minimize the possibility to hedge, for one game protocol subjects were paid based on their actions and for the second game protocol they were paid based on the accuracy of their beliefs. For the payment based on actions, subjects were randomly matched in pairs and randomly assigned the role of first-mover or second-mover. Based on the actions in a pair, earnings for both subjects in the pair were calculated. For the payment based on beliefs, one decision node was randomly selected and subjects were paid using a quadratic scoring rule.

At the beginning of each session, subjects were randomly assigned a cubicle and read the instructions on-screen at their own pace. Subjects also received a printed summary of the instructions. At the end of the instructions subjects had to successfully complete a quiz to test their understanding of the instructions before they could continue. After completing the game protocols, we elicited risk attitudes using an incentivized method similar to the method of Eckel and Grossman (2002). Self-reported demographic data was gathered by way of asking the subjects to complete a short questionnaire at the end of the session. The instructions, quiz questions and risk elicitation task are reproduced in Appendix A7. Sessions took around 1 hour and subjects earned between €10.50 and €26.90 with an average of €18.80. Key features of the experimental design and main analyses were pre-registered.[14]

[13] The literature on whether and how eliciting beliefs affects decisions provides mixed evidence. In Public Goods games for example, Croson (2000) finds that eliciting beliefs decreases contributions, while Gächter and Renner (2010) find that eliciting beliefs *increases* contributions and Wilcox and Feltovich (2000) find no effect of eliciting beliefs.

[14] See https://aspredicted.org/blind.php?x=4u5nu8 and Appendix A6. We pre-registered the type of game protocols (SPDs, TGs, UGs), the sample size, the main parameters of interest (α, β, κ), and using a logit model to estimate these parameters.

In Table 1, we present an overview of the average actions and beliefs for each game protocol. On average, observed behavior follows patterns that accord well with other experiments. For example, in the SPDs, on average subjects display conditional cooperation ($x_2 > x_3$). In the TGs, increasing the temptation payoff T and decreasing the sucker payoff S (compare game protocols 7 vs 8, 9 vs 10, 11 vs 12) reduces both trust (x_1) and trustworthiness (x_2). In the UGs, lower offers (P) are accepted less frequently (x_2). Moreover, on average actions (x) and beliefs (y) are highly correlated (see also Figure A.1 in Appendix A1). Table A.1 in Appendix A1 presents all decisions in the risk elicitation task. Based on their lottery choice, most subjects (83%) are classified as being risk-averse.

2.4 Distinguishing Kantian morality from social preferences

Many experimental studies use dictator game protocols to estimate social preferences. An advantage of such protocols is that they contain no strategic element, and hence there is no need to elicit subjects' beliefs about other subjects' behaviors. However, this class of game protocols would not allow us to distinguish between social preferences and Kantian morality à la *Homo moralis*. To see why, consider a dictator game in which the donor may transfer any part of his endowment w to the recipient, and the amount transferred will be multiplied by a factor $m > 1$.[15] Suppose that both players face an equal probability of being the donor, and denote by $x \in [0, w]$ and $y \in [0, w]$ their respective strategies (how much to give in the donor role). Consider first a pure altruist i, with $\beta_i = -\alpha_i \geq \kappa_i = \delta_i = 0$, and thus a utility function of the form (the factor $1/2$ represents nature's draw of roles):

$$u_i(x, y) = \frac{1}{2}[(1 - \beta_i)(w - x + my) + \beta_i(mx + w - y)]. \quad (2)$$

[15] The same argument applies if $m = 1$ as long as the subject's marginal utility from money is decreasing.

If instead i is a pure *Homo moralis*, with $\kappa_i \geq \alpha_i = \beta_i = \delta_i = 0$, then his or her expected utility is:

$$u_i(x,y) = \frac{1}{2}[(1-\kappa_i)(w-x+my)+\kappa_i(mx+w-x)]. \tag{3}$$

Comparison of the second terms in these utility functions reveals that while an altruist cares about the other individual's monetary payoff $(mx+w-y)/2$ (which depends on the other's strategy y), an individual driven by Kantian morality instead cares about the monetary payoff $(mx+w-x)/2$, which would result if both players were to use i's strategy x. Nonetheless, as shown by the derivatives with respect to own strategy x, the trade-off for altruists and Kantian moralists is the same here:

$$\frac{du_i(x,y)}{dx} = \frac{1}{2}[\beta_i m-(1-\beta_i)], \tag{4}$$

and

$$\frac{du_i(x,y)}{dx} = \frac{1}{2}(\kappa_i m-1). \tag{5}$$

Whether an altruist or a Kantian moralist, the individual either gives the whole endowment or nothing at all: indeed, dividing the right-hand side of (4) by $1-\beta_i$, and letting $\sigma_i \equiv \frac{\beta_i}{1-\beta_i}$, we see that the altruist gives everything if σ_i exceeds $1/m$ while the Kantian moralist gives everything if κ_i exceeds $1/m$.[16] Therefore, we would be unable to separate altruism from a Kantian concern using dictator games.[17]

[16] This observation is in line with a more general comparison of behavioral predictions for altruists and Kantian moralists in Alger and Weibull (2013), see also Alger and Weibull (2017).

[17] We would face the same identification problem with allocation tasks. Consider a subject i who faces the choice between the allocations (S,T) and (P,P), where the first entry is monetary payoff to self and the second entry is monetary payoff to the other subject, with $T > P > S$. A risk-neutral subject i with a utility function of the form in (1) strictly prefers (S,T) to (P,P) if and only if $\kappa_i(T-P)-\alpha_i(T-S) > P-S$. Hence, a subject who selects (S,T) can be driven either by pure altruism $(-\alpha_i > 0 = \kappa_i)$, by pure Kantian morality $(\kappa_i > 0 = \alpha_i)$, by a combination of these, or by a combination of behindness aversion and Kantian morality $(\kappa_i > \alpha_i > 0)$.

By instead using game protocols that contain strategic elements and collecting data on decisions at all nodes in the game tree as well as beliefs about opponent's play, our experimental design allows us to discriminate between social and Kantian moral preferences. The key effect is that an individual with a Kantian moral concern is not only influenced by his belief about the opponent's actual play, but also by what he would himself have done had the player roles been reversed (information that we collect in the experiment). Put differently, an important consequence of Kantian morality is that a subject's preferences over moves off the equilibrium path associated with a strategy pair (x, y) may influence his or her decisions on its path. This differs sharply from altruism, inequity aversion or spite, which induce consequentialistic reasoning.

While we provide a more detailed analysis for the three game protocols in the Appendix A2, here we describe the key difference between social preferences and Kantian morality by considering a (symmetrically randomized) Trust Game protocol (see Figure 1b) with $2R > T + S$. Suppose that an individual i believes that the opponent will play K ("keep") as second-mover and I ("invest") as a first-mover. The conditions for i to choose I as first-mover and G ("give back") as second-mover, respectively, are then:[18]

$$(1-\kappa_i)(S-P)-\alpha_i(T-S)+\kappa_i 2(R-P)\geq 0 \tag{6}$$

$$(1-\kappa_i)(R-T)+\beta_i(T-S)+\kappa_i(2R-S-T)\geq 0. \tag{7}$$

Suppose the individual has no Kantian morality ($\kappa_i = 0$). Whether selfish or driven by behindness aversion ($\alpha_i > 0$), he selects N as first-mover (as implied by (6)), so that the conditions cannot be met. Furthermore, he would need to be sufficiently averse to being ahead ($\beta_i > 0$) to refrain from choosing K as second-mover (as implied by (7)). Now suppose instead that $\kappa_i > 0$. For the choice as first-mover, Kantian morality makes this

[18] These conditions are implied by the expressions (23) and (24) in Appendix A2. Note that even if the term that multiplies κ_i in (7), i.e., $2R - S - T$, is nil, these payoffs would still have an effect on the decision to choose I as first-mover, as seen in (6).

individual evaluate the material payoff he would obtain from selecting I instead of N, given that he would choose G as second-mover and under the hypothetical scenario that the opponent would also pick G as second-mover: this equals $R-P$ (the factor 2 comes from the omitted probability 1/2). The third term in (6) outweighs the first two for κ_i sufficiently large. Turning now to the choice as second-mover, a positive κ_i makes the individual evaluate the increase in expected material payoff (the expectation being taken over the two player roles) he would obtain if he as well as the opponent (hypothetically) were to choose G rather than K as second-mover, given that he himself picks I as first-mover: this equals $\frac{1}{2}(R-S)+\frac{1}{2}(R-T)$ (the probability 1/2 has been omitted in (7)). For κ_i sufficiently large, the third term in (7) outweighs the first two terms. In sum, for a large enough κ_i, the individual chooses I as first-mover and G as second-mover, even though he believes that the opponent will play K as second-mover.

Two important implications appear from conditions (6) and (7). First, payoffs off-the-equilibrium path may matter: for example, condition (6) shows that a change in the payoff R (which is off the equilibrium path if the individual at hand moves first and his beliefs about his opponent are correct) can make the individual switch from N to I. Second, condition (7) reveals that in a model where the Kantian moral concern is omitted, an individual must be averse to being ahead ($\beta_i > 0$) for him to choose G. By contrast, an individual with a positive degree of morality $\kappa_i > 0$ may choose G even if $\beta_i = 0$. In fact, if κ_i is large enough, he can even be spiteful ($\beta_i < 0$) and still choose G.

Table 2 shows some behavioral predictions, assuming either self-interest ($\alpha_i = \beta_i = \delta_i = \kappa_i = 0$), behindness aversion ($\alpha_i = 0.4$, $\beta_i = \delta_i = \kappa_i = 0$), altruism ($\alpha_i = -0.2, \beta_i = 0.5$, $\delta_i = \kappa_i = 0$), a combination of altruism and reciprocity ($\alpha_i = -0.2, \beta_i = 0.5$, $\delta_i = 0.4, \kappa_i = 0$), or Kantian morality ($\alpha_i = \beta_i = \delta_i = 0$, $\kappa_i = 0.2$). The behindness averse and altruistic types qualitatively resemble the behindness averse and (strongly) altruistic type estimated by Bruhin et al. (2019).

All types display different behavior. In the Sequential Prisoner's Dilemma protocols,

both self-interest and behindness aversion lead to unconditional defection as a second mover, but self-interested types will more frequently (opportunistically) cooperate as a first mover. An altruist will frequently unconditionally cooperate as a second mover, unless defection after cooperation leads to higher joint payoffs (SPD 1), or when punishment becomes sufficiently attractive (SPD 6). When enriching altruism with reciprocity, conditional cooperation emerges. Likewise, an individual motivated by Kantian morality ("*Homo moralis*") will typically conditionally cooperate, unless the benefits to join cooperation become too small (SPDs 1 and 2). In particular, note that if $S + T > 2R$ (as in SPD 1), the convex combination of self-interest and Kantian morality entails a behavior not seen in any of the other types. By contrast to self-interest and behindness aversion, the Kantian moral concern entails a second-mover behavior that maximizes the expected material payoff from an *ex ante* perspective (i.e., cooperate following defection and *vice versa*). However, by contrast to the altruistic type in Table 2, which also selects this second-mover behavior, the type that combines self-interest and Kantian morality defects as a first mover: given that such an individual would cooperate as a second-mover following defection, both the self-interest part and the Kantian part of the utility function indeed entails a wish to defect.

The behavior of those motivated by Kantian morality differs even more strongly from those exhibiting a combination of altruism and reciprocity in the Trust Game and Ultimatum Game protocols. In the Trust Game protocols, (strong) altruists will always invest (I) as first mover and "give back" (G) as a second mover, while individuals motivated by Kantian morality will play "keep" (K) when R is relatively low.[19] In the Ultimatum Game, those motivated by Kantian morality will make unequal offers (U) and accept any offer (A), while those motivated by altruism and negative reciprocity will propose equal splits (E) and refuse low offers (F, UGs 17 and 18).

[19] Only when $\kappa = 1$, an individual motivated by Kantian morality would always choose (I, G).

Table 2: Behavioral predictions

No.	T	R	P	S	self-interest $\alpha=0$ $\beta=0$ $\delta=0$ $\kappa=0$	behindness aversion $\alpha=0.4$ $\beta=0$ $\delta=0$ $\kappa=0$	altruism $\alpha=-0.2$ $\beta=0.5$ $\delta=0$ $\kappa=0$	altruism + reciprocity $\alpha=-0.2$ $\beta=0.5$ $\delta=0.4$ $\kappa=0$	homo moralis $\alpha=0$ $\beta=0$ $\delta=0$ $\kappa=0.2$
Sequential Prisoner's Dilemmas									
1	90	45	15	10	(D,D,D)	(D,D,D)	(C,D,C)	(C,D,C)	(D,D,C)
2	90	55	20	10	(D,D,D)	(D,D,D)	(C,C,C)	(C,C,D)	(C,D,D)
3	80	65	25	20	(C,D,D)	(D,D,D)	(C,C,C)	(C,C,D)	(C,C,D)
4	90	65	25	10	(C,D,D)	(D,D,D)	(C,C,C)	(C,C,D)	(C,C,D)
5	80	75	30	20	(C,D,D)	(C,D,D)	(C,C,C)	(C,C,D)	(C,C,D)
6	90	75	30	10	(C,D,D)	(D,D,D)	(C,C,D)	(C,C,D)	(C,C,D)
Trust Games									
7	80	50	30	20	(N,K)	(N,K)	(I,G)	(I,G)	(I,K)
8	90	50	30	10	(N,K)	(N,K)	(I,G)	(I,G)	(N,K)
9	80	60	30	20	(I,K)	(N,K)	(I,G)	(I,G)	(I,K)
10	90	60	30	10	(N,K)	(N,K)	(I,G)	(I,G)	(I,K)
11	80	70	30	20	(I,K)	(I,K)	(I,G)	(I,G)	(I,G)
12	90	70	30	10	(I,K)	(N,K)	(I,G)	(I,G)	(I,G)
Ultimatum Games									
13	60	50	40	10	(U,A)	(U,A)	(E,A)	(E,A)	(U,A)
14	65	50	35	10	(U,A)	(U,A)	(E,A)	(E,A)	(U,A)
15	70	50	30	10	(U,A)	(U,A)	(E,A)	(E,A)	(U,A)
16	75	50	25	10	(U,A)	(U,F)	(E,A)	(E,A)	(U,A)
17	80	50	20	10	(U,A)	(U,F)	(E,A)	(E,F)	(U,A)
18	85	50	15	10	(U,A)	(U,F)	(E,A)	(E,F)	(U,A)

Notes: Predicted behavioral strategies, assuming rational expectations and risk neutrality (see Table 1 for average play in each game protocol).

3 Statistical analysis

The econometric strategy consists in producing both individual and aggregate estimates of the parameters in the utility function specified in (1) using a random utility model. In the main specification we employ subjects' stated beliefs (note that this implies that no equilibrium assumption is needed). We will then conduct several robustness checks and propose ways to evaluate the value-added of including Kantian morality.

3.1 Individual preferences

For each subject i, we estimate the individual's social and moral preference parameters α_i, β_i, δ_i, and κ_i as specified in (1), using a standard additive error specification. We refer to these preference parameters using the vector $\theta_i = (\alpha_i, \beta_i, \delta_i, \kappa_i)$. We consider pure strategies (that is, assigning a unique action at each decision node), and assume that subject i's true (expected) utility from using pure strategy x_i when $\hat{y}_i$ is i's expectation about his opponents behavior, is a random variable of the additive form

$$\tilde{u}_i(x_i, \hat{y}_i, \theta_i) = u_i(x_i, \hat{y}_i, \theta_i) + \varepsilon_{ix_i},$$

where $u_i(x_i, \hat{y}_i, \theta_i)$ is the expected utility of using strategy x_i given beliefs $\hat{y}_i$ following from the utility function in (1), and ε_{ix_i} is a random variable representing idiosyncratic tastes not picked up by the hypothesized utility $u_i(x_i, \hat{y}_i, \theta_i)$. Such a random utility specification sometimes induces choice of actions that do not maximize the deterministic component $u_i(x_i, \hat{y}_i, \theta_i)$. Assuming that the noise terms ε_{ix_i} are statistically independent (between subjects and across pure behavior strategies x_i for each subject) and Gumbel distributed with the same variance, the probability that subject i will use strategy x_i, given his probabilistic belief $\hat{y}_i$ about the opponent's play is given by the familiar logit formula

(McFadden, 1974):

$$p_i(x_i, \hat{y}_i, \theta_i, \lambda_i) = \frac{\exp\left[(u_i(x_i, \hat{y}_i, \theta_i))/\lambda_i\right]}{\sum_{x' \in X_g} \exp\left[(u_i(x', \hat{y}_i, \theta_i))/\lambda_i\right]}, \tag{8}$$

where $\lambda_i > 0$ is a "noise" parameter, which is estimated alongside the preference parameters in θ_i, and X_g denotes the set of pure strategies in game protocol $g \in G$, where G is the set of game protocols. The smaller the parameter λ_i is, the higher is the probability that individual i makes his or her choices according to the hypothesized utility function $u_i(x_i, \hat{y}_i, \theta_i)$. We use maximum likelihood to estimate the preference parameter vector $\theta_i = (\alpha_i, \beta_i, \delta_i, \kappa_i)$ and the "noise" parameter λ_i for each individual i.[20] Then, the probability density function can be written as:

$$f(\mathbf{x}_i, \hat{\mathbf{y}}_i, \theta_i, \lambda_i) = \prod_{g \in G} \prod_{x \in X_g} p_i(x, \hat{y}_i, \theta_i, \lambda_i)^{I(i,g,x)}, \tag{9}$$

where $\mathbf{x}_i$ is the vector of the observed pure strategies of individual i, $\hat{\mathbf{y}}_i$ is the vector of stated beliefs of individual i about opponent's strategy in all the game protocols, and $I(i, g, x)$ is an indicator function that equals 1 if i played strategy x in game protocol g and 0 otherwise.

3.2 Aggregate estimations

We estimate preference parameters both for a representative agent and a given number of "preference types". For the representative agent, we simply aggregate all individual decisions and treat them as if they come from a single decision-maker. For the types estimations, we use finite mixture models, similar to the approach used by Bruhin et al. (2019). The finite mixture estimations allow us to capture heterogeneity in the population in a tractable way. For these estimations, we assume that there is a given number of

[20] In the maximum likelihood estimations, we use 6 different starting values for each parameter, so for the model with all five parameters $(\alpha_i, \beta_i, \delta_i, \kappa_i, \lambda_i)$, we use $6^5 = 7{,}776$ starting values per individual i.

types K in the population. For each type $k = \{1, ..., K\}$, we estimate the parameter vector $\theta_k = (\alpha_k, \beta_k, \delta_k, \kappa_k)$ and the noise parameter λ_k. The log-likelihood is then given by:

$$\ln L = \sum_{i=1}^{N} \ln \left(\sum_{k=1}^{K} \phi_k \cdot f(\mathbf{x}_i, \hat{\mathbf{y}}_i, \theta_k, \lambda_k) \right), \tag{10}$$

where ϕ_k is the population share of type k in the population. To maximize the log-likelihood in (10), we use an Expectation-Maximization (EM) algorithm (see for instance McLachlan, Lee, & Rathnayake, 2019).[21] As part of the EM algorithm, we estimate the posterior probabilities $\tau_{i,k}$ that individual i belongs to type k by:

$$\tau_{i,k} = \frac{\phi_k \cdot f(\mathbf{x}_i, \hat{\mathbf{y}}_i, \theta_k, \lambda_k)}{\sum_{m=1}^{K} \phi_m \cdot f(\mathbf{x}_i, \hat{\mathbf{y}}_i, \theta_m, \lambda_m)}. \tag{11}$$

4 Results of pre-registered analyses

The main analyses that we pre-registered were to estimate α_i, β_i, and κ_i, and to compare the predictive value of this model to restricted versions of the model (the pre-registration is reproduced in Appendix A6). In the following section, we present the results of these analyses assuming that subjects are risk neutral.[22] In section 5, we perform several robustness analyses by allowing for risk aversion, rational expectations, or game protocol type specific noise parameters. Finally, in section 6, we will extend the pre-registered model to allow for reciprocity (δ) and compare the added value of α, β, and κ, as well as δ.

[21] We use 24 sets of starting values.

[22] In the estimations, we use the CRRA functions in equations (15) and (16) that we will discuss in section 5, and impose $r = 0$.

Table 3: Individual parameter estimates

Parameter	Median	Mean	S.D.	Min	Max
α_i	0.11	0.16	0.20	−0.19	1.06
β_i	0.19	0.15	0.37	−1.55	1.08
κ_i	0.10	0.13	0.14	−0.16	0.72

Notes: Table based on the 112 subjects for whom the α_i, β_i and κ_i estimates have absolute value below 2. Table A.2 shows a similar table based on all 136 subjects.

4.1 Individual preferences

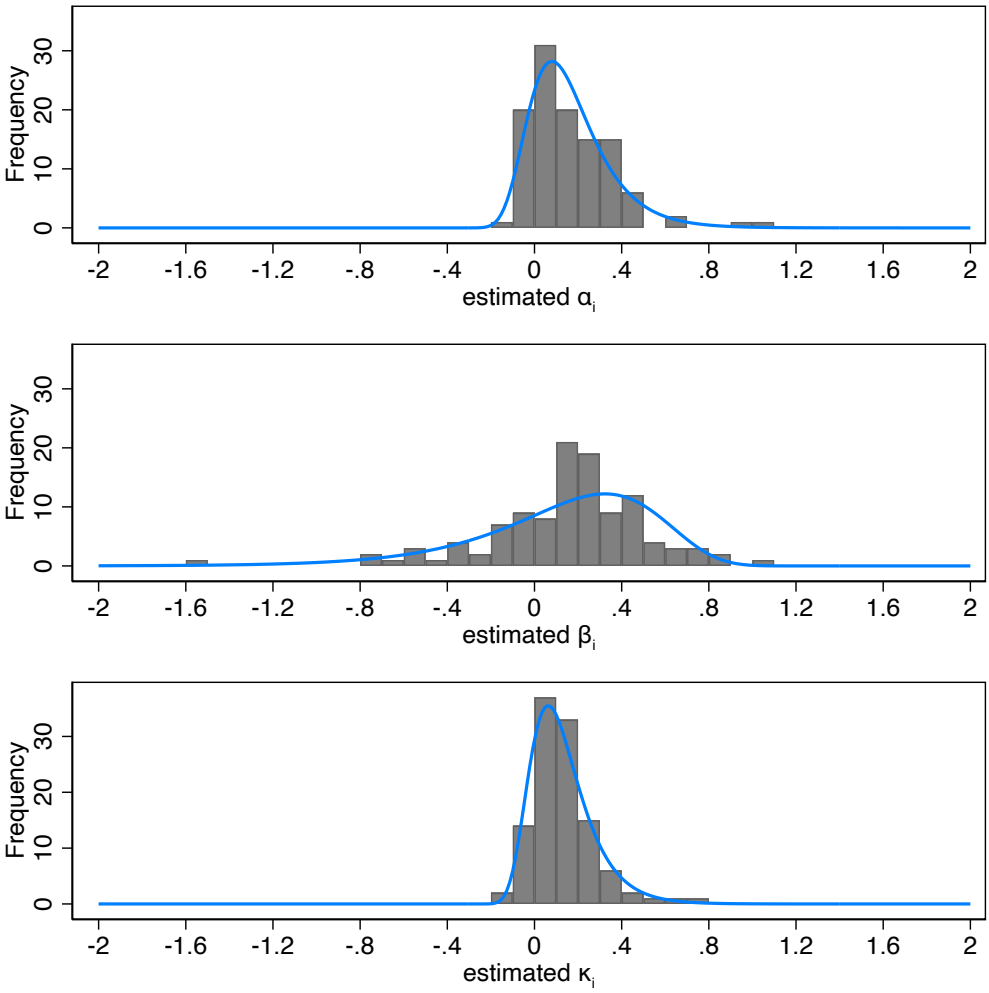
Figure 3 shows the marginal distributions of the estimated individual preference parameters α_i, β_i, and κ_i for our core sample of 112 subjects.[23] For all three parameters, we observe considerable heterogeneity. Most estimates of α_i, β_i, and κ_i are positive and signed-ranks tests confirm that the parameter distributions are located to the right of zero ($p < 0.001$ for either α_i, β_i, and κ_i estimates).

Table 3, which shows summary statistics for the parameter estimates, provides further support for the pattern observed in Figure 3. Median and mean estimates are positive for α_i, β_i and κ_i. Moreover, the relatively large standard deviations indicate that there is considerable heterogeneity in social preferences and Kantian morality.

Figure 4 illustrates the pairwise correlations between the three preference parameter estimates. The left panel of Figure 4 shows that the estimates for α_i and β_i are negatively correlated (Spearman's $\rho = -0.257$, $p = 0.006$, $n = 112$). For many individuals we observe a combination of $\alpha_i > 0$ and $\beta_i > 0$, in line with inequality averse preferences. However, we also observe a number of individuals for whom $\alpha_i > 0$ and $\beta_i < 0$, in line

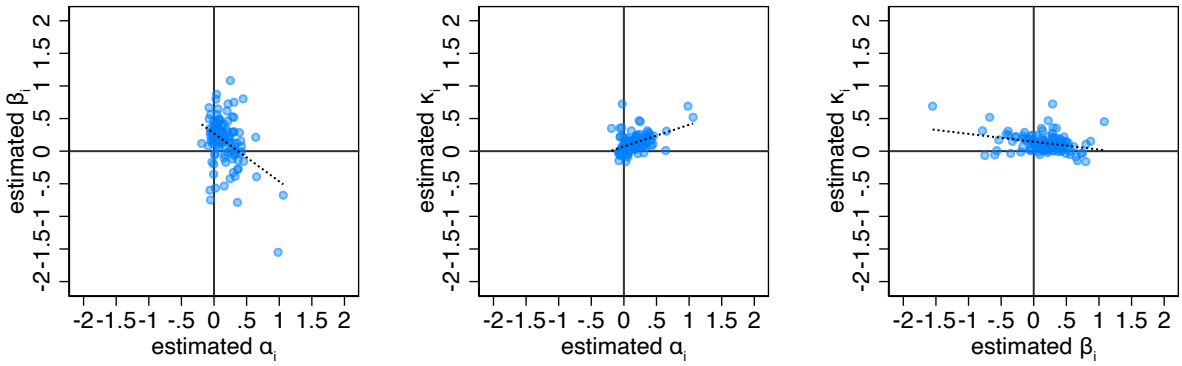
[23] In the estimations, we do not restrict the size or the sign of the parameter estimates. For most subjects, the parameter estimates are of reasonable size. However, for some subjects we obtain very large estimates of α_i, β_i, and/or κ_i (in absolute value), suggesting that our utility function (1) does not explain the decisions of these subjects well, either because they use a decision rule not nested in (1), or because their decisions are simply too noisy to be generated by any utility function. In the remainder of this section, we report results for our 'core sample', which consists of the 112 subjects for whom all three preference parameter estimates lie between -2 and 2. The fraction that we leave out in the main text (17.6%) is comparable in size to the fraction of 26.3% for whom Fisman et al. (2007) conclude that their decisions are too noisy to be utility-generated. In Appendix A1 we report results based on data for all 136 subjects. While the latter results are more noisy, they are qualitatively quite similar to those for the core sample.

Figure 3: Distributions of individual parameter estimates



Note: Figure based on the 112 subjects for whom the α_i, β_i and κ_i estimates have absolute value below 2. The (blue) lines indicate fitted Gumbel distributions (see Appendix A3 for details). Figure A.2 shows a similar figure based on all 136 subjects.

Figure 4: Correlations between estimated preference parameters



Notes: Each dot represents one subject. Dotted lines indicate linear predictions (intercept+slope). Specifically, we estimate $\beta_i = 0.27 - 0.73\alpha_i$, $\kappa_i = 0.07 + 0.33\alpha_i$, $\kappa_i = 0.14 - 0.12\beta_i$. Figure based on the 112 subjects for whom the α_i, β_i and κ_i estimates have absolute value below 2.

with spiteful or competitive preferences. The middle panel of Figure 4 reveals a strong and positive correlation between α_i and κ_i estimates (Spearman's $\rho = 0.432$, $p < 0.001$, $n = 112$). This means that many individuals combine a distaste for behindness aversion with Kantian morality. For the estimates of β_i and κ_i we find a negative correlation (Spearman's $\rho = -0.238$, $p = 0.011$, $n = 112$). We also use copula methods to describe the joint parameter distributions for the individual estimates of α_i, β_i and κ_i. As for the pairwise correlations reported above, we observe that the individual estimates of α_i, β_i and κ_i are not statistically independent. Appendix A3 provides more details.

4.2 Aggregate estimations

We now turn to estimation of preferences at the aggregate level (see section 3.2 for details). To distinguish these estimates from the individual ones, we use an index k to designate the type. Table 4 presents the estimates of the finite mixture models for one, two and three types.

Table 4: Estimates at the aggregate level

	1 type	2 types		3 types		
	Rep. agent	Type 1	Type 2	Type 1	Type 2	Type 3
α_k	0.16	0.12	0.18	0.18	0.01	0.17
	(0.01)	(0.02)	(0.02)	(0.03)	(0.04)	(0.02)
β_k	0.24	0.35	0.00	0.27	0.47	0.00
	(0.03)	(0.04)	(0.04)	(0.06)	(0.06)	(0.04)
κ_k	0.10	0.10	0.10	0.11	0.15	0.09
	(0.01)	(0.02)	(0.01)	(0.02)	(0.04)	(0.01)
λ_k	7.19	8.44	3.96	8.83	6.47	3.68
	(0.47)	(0.66)	(0.54)	(0.94)	(1.00)	(0.25)
ϕ_k	1.00	0.62	0.38	0.48	0.17	0.36
	(-)	(0.07)	(0.07)	(0.07)	(0.06)	(0.05)
$\ln L$	-2441.1	-2254.4			-2225.3	
$EN(\boldsymbol{\tau})$	0.00	6.06			15.16	
ICL	4901.1	4557.3			4531.9	
NEC	-	0.032			0.070	

Notes: Bootstrapped standard errors in parentheses. Table based on our 'core sample' of 112 subjects. Table A.3 in Appendix A1 shows estimates based on the full sample. Table A.4 in Appendix A1 shows the estimates of a 4-type model.

4.2.1 The representative agent

When assuming only one type, that is, a representative agent, we obtain the estimates $\alpha_0 = 0.16$, $\beta_0 = 0.24$, and $\kappa_0 = 0.10$, where the index 0 stands for the representative agent. In other words, the representative agent dislikes both disadvantageous and advantageous inequity, and has a positive degree of Kantian morality. The representative agent thus exhibits Kantian morality and inequity aversion.

4.2.2 The two- and three-type models

As can be seen in Table 4, in both multi-type models all types exhibit Kantian morality ($\kappa_k > 0$), roughly of the same order of magnitude as the representative agent. There is stronger heterogeneity in terms of the inequity aversion parameters α_k and β_k: in particular, some types exhibit only behindness aversion ($\alpha_k > 0$), some exhibit only aheadness aversion ($\beta_k > 0$), while some exhibit a combination of the two.

More specifically, when assuming two types, the most common type (Type 1) exhibits inequity aversion, with parameter estimates $\alpha_1 = 0.12$ and $\beta_1 = 0.35$, combined with a degree of Kantian morality $\kappa_1 = 0.10$. This type represents about 62% of the subjects. The other type, Type 2, exhibits a combination of behindness aversion and Kantian morality, with $\alpha_2 = 0.18$, $\beta_2 = 0.00$, and $\kappa_2 = 0.10$.

For each subject i, we estimate the posterior probability $\tau_{i,k}$ that i belongs to type k (as defined in (11)). By taking the largest value $\tau_{i,k}$ for each subject i, we can assign each of the subjects to one of the types. Table A.5 in Appendix A1 lists the chosen strategies per game protocol type based on this classification. "Type 2 subjects", who combine behindness aversion and Kantian morality, mostly choose to always defect (D, D, D) in the SPDs (in 84% of the cases), while "Type 1 subjects", who combine inequity aversion and Kantian morality, choose (D, D, D) less frequently (40%) and often conditionally cooperate (C, C, D) instead (30%). Similarly, in the TGs, Type 2 subjects most frequently choose not to invest as first mover and to "keep" as second mover (N, K) (83%), while Type 1 subjects most frequently invest as first mover and "give" as a second mover (I, G) (43%). In the UGs, Type 2 subjects mostly choose the unequal option as a first mover (75%) and accept unfair offers as a second mover (97%). Instead, Type 1 subjects most frequently propose an equal payoff (66%) and accept fewer unequal offers (90%).

When assuming three types, for all types we again estimate a positive Kantian morality parameter κ_k. In comparison with the results under the two-types approach, Type 3 is very close to the previous Type 2. This type is again characterized as combining behindness aversion with Kantian morality, and represents a similar fraction of the population (36%).[24] The new Type 2 combines (relatively strong) aheadness aversion with Kantian morality. It represents around 17% of the population. As in the two-types model, Type 1 in the three-types model combines inequity aversion with Kantian morality. This type

[24] In panel A of Table A.6 (see Appendix A1), we show a transition matrix for the two-types and three-types models. All but three subjects who are classified as Type 2 in the two-types model, are classified as Type 3 in the three-types model. All subjects who were classified as Type 1 in the two-types model are now distributed across the new Types 1 and 2.

represents 48% of the population. In sum: under the three-types approach, Type 1 displays a combination of inequity aversion and Kantian morality, Type 2 is aheadness averse and moral, and Type 3 is behindness averse and moral.

In terms of chosen strategies, Type 3 behaves almost identical as Type 2 in the two-types model. The new Type 1 and Type 2 differ in some respects. In the SPDs, the new Type 2 acts conditionally cooperative more often than Type 1. Similarly, Type 2 chooses to "give" more often than Type 1 in the TGs. In the UGs, Types 1 and Type 2 behave quite similarly.

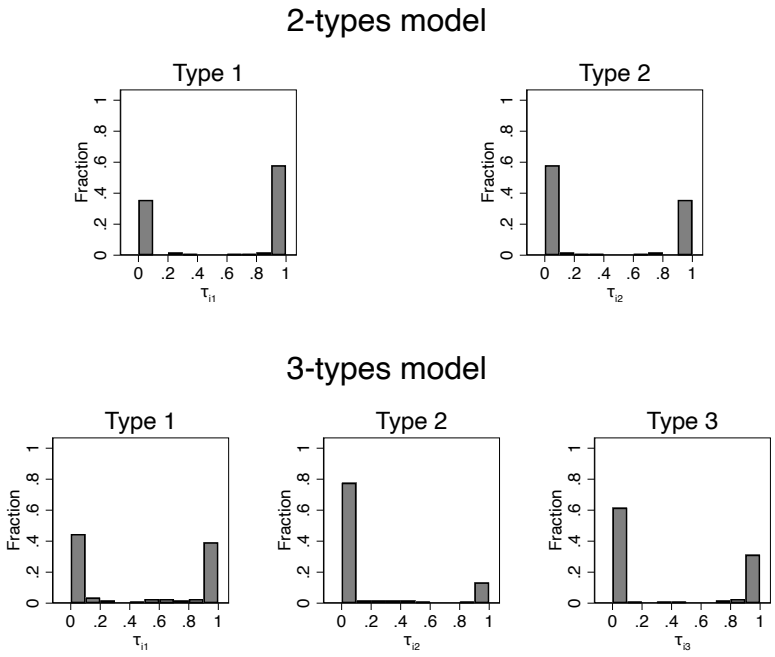
In sum, the aggregate estimates lead to two observations. First, we observe relatively little heterogeneity in estimates of the morality parameter κ_k. In most cases, κ_k is around 0.1, showing that most people are well described by having Kantian morality concerns. Second, we note that in both multi-type models, we do not observe types who are best described by pure self-interest ($\alpha_k = \beta_k = \kappa_k = 0$). This is in line with the findings by Bruhin et al. (2019). Nonetheless, self-interest is still an important driver for all the types.

4.2.3 Comparing the one-, two-, and three-types models

Clearly, adding more types improves the fit of the model, but this comes at the cost of parsimony as well as precision of allocating individuals to types. Information criteria like the Bayesian information criterion (BIC) are not well suited to select the number of clusters (or in our case, 'types') in finite mixture models. In a recent overview paper on the use of finite mixture models, McLachlan et al. (2019) recommend using the 'integrated completed likelihood' (or 'integrated classification', ICL, Biernacki, Celeux, & Govaert, 2000). This criterion is approximated by

$$ICL = -2\ln L + d\ln N + EN(\boldsymbol{\tau}), \tag{12}$$

Figure 5: Posterior probabilities of type classifications



Notes: Distributions of the estimated posterior probability $\tau_{i,k}$ of individual i belonging to type k for the two-types and three-types finite mixture models reported in Table 4.

where the log-likelihood function $\ln L$ is defined as in (10), d is the number of estimated parameters, and N is the number of individuals in our sample. The last term in (12) is the entropy

$$EN(\boldsymbol{\tau}) = -\sum_{k=1}^{K}\sum_{i=1}^{N} \tau_{i,k} \ln \tau_{i,k}, \tag{13}$$

where $\tau_{i,k}$ is the estimated posterior probability of individual i belonging to type k, as defined in (11). This implies that the stronger individuals are assigned to types (i.e. all $\tau_{i,k}$'s close to zero or one), the lower the entropy will be. In other words, the ICL extends the BIC by adding an additional penalty if individuals are assigned imprecisely to types.

Figure 5 shows the distributions of the estimated posterior probability $\tau_{i,k}$ (of individual i belonging to type k) for the two-type and three-type models. In all cases, most estimated $\tau_{i,k}$ are very close to zero or 1, which implies that most individuals are quite precisely assigned to a type. For the two-types model, virtually all estimated $\tau_{i,k}$ are close

to zero or one. For the three-types model, a few individuals are imprecisely classified.

Bruhin et al. (2019) use the 'normalized entropy criterion' (NEC, Celeux & Soromenho, 1996), which is defined as:

$$NEC = \frac{EN(\boldsymbol{\tau})}{\ln L(K) - \ln L(1)}, \tag{14}$$

where $\ln L(1)$ is the log-likelihood of the representative agent model and $\ln L(K)$ the log-likelihood of the model with K types. Hence, the NEC weighs the precision of the type classifications $\tau_{i,k}$ by the increase in the log-likelihood compared to the representative agent model.

Table 4 shows statistics for both the ICL and the NEC. For both metrics, a lower score indicates a more preferred model. The NEC selects the two-types model and the ICL selects the three-types model. Table A.4 in Appendix A1 shows estimates and goodness-of-fit metrics for a four-types model. The four-types model performs worse on both criteria than the three-types models in Table 4. Note that marginal improvement in the ICL score is largest when going from the representative agent to the two-types model. In sum, assuming two types instead of a representative agent brings us a long way in capturing the heterogeneity in the population.

5 Robustness

In this section, we describe additional (not pre-registered) analyses where we allow for risk aversion, or where we impose rational expectations rather than using the subjective beliefs elicited in the experiment, or where we allow for different noise parameters λ for each type of game protocol. Here we discuss the main findings; more details are provided in Appendix A4.

5.1 Risk attitudes

In the main analysis, we imposed risk neutrality. However, since each subject in our experiment faces risky decisions (the monetary payoff depends on the decision of the opponent, which the subject does not know when making the decisions), we here report estimations allowing for risk aversion.[25] Thus, we will here take the term $\pi_i(\gamma)$ in the utility function in (1) to be the Bernoulli function value that the individual attaches to his or her monetary payoff under play γ. If the monetary payoff allocation after a play γ is $\left(m_i(\gamma), m_j(\gamma)\right)$, we assume that the individual's own material utility is of the CRRA form

$$\pi_i(\gamma) = \frac{m_i(\gamma)^{1-r_i} - 1}{1 - r_i}, \tag{15}$$

where r_i is the (constant) *degree of relative risk aversion* of subject i. We further assume that each subject evaluates his or her opponent's monetary payoff in terms of own risk attitude.[26] Hence, subject i evaluates the opponent j's monetary payoff as follows:

$$\pi_j^i(\gamma) = \frac{m_j(\gamma)^{1-r_i} - 1}{1 - r_i}. \tag{16}$$

Risk neutrality is the special case when $r_i = 0$, and we identify the special case $r_i = 1$ with logarithmic utility for money: then $\pi_i(\gamma) = \ln m_i(\gamma)$ and $\pi_j^i(\gamma) = \ln m_j(\gamma)$.

In a recent paper, Apesteguia and Ballester (2018) show that estimating CRRA parameters using a random utility model may be problematic. To avoid this, we estimate the social preference and Kantian morality parameters imposing risk parameters. At the

[25] Following Rabin (2000), expected utility theory may not be best-suited to capture small-stakes risk aversion, and behavior in line with risk aversion may also be explained by other sources as loss aversion or mental accounting (Rabin & Thaler, 2001). Our experiment is not designed to disentangle different sources, however.

[26] There is experimental evidence that both students and financial professionals exhibit such false consensus (Roth & Voskort, 2014). Moreover, there is experimental evidence that people make the same decisions under risk (in the gain domain) for themselves and others (Andersson, Holm, Tyran, & Wengström, 2014; Exley, 2016), although Exley (2016) also shows that people sometimes act more averse to risk for others if it is in their material self-interest to do so. Gauriot, Heger, and Slonim (2020) show through simulations that estimates of social preferences parameters may depend on how subjects evaluate the monetary payoffs of others.

individual level, we infer the risk parameter r_i from the lottery choices in the Eckel and Grossman (2002) task (see Table A.1 in Appendix A1). At the aggregate level, we estimate mixture models under the assumption that all subjects have logarithmic utility over monetary outcomes (i.e. we impose $r_k = 1$ for all types k).

At the individual level, the respective parameter estimates under risk neutrality and CRRA preferences are strongly correlated (see Appendix A4.1 for a detailed analysis). Under CRRA preferences however, we observe a substantial directional shift in the estimates of β_i compared to the risk-neutral case. While most estimates of β_i are positive under risk neutrality, most estimates of β_i are negative under CRRA preferences. There is also a shift in the estimates of κ_i towards higher values.

Table 5 shows the estimates of finite mixture models under logarithmic utility. Comparing these results with those in Table 4, one sees that, qualitatively, estimates of the parameters α_k and κ_k are not much affected, although the Kantian morality parameter values are higher under CRRA than under risk neutrality. In line with the individual parameter estimates, the finite mixture estimates of the parameters β_k tend to be higher under risk neutrality than under CRRA. Moreover, under risk neutrality, all estimates of β_k are non-negative, in contrast to the CRRA estimates, where we observe $\beta_k < 0$ for some types k.[27] To see why risk aversion leads to lower degrees of aheadness aversion—sometimes even aheadness loving—than under risk neutrality, consider the Ultimatum Game protocol. In the Ultimatum Game, both risk aversion and aheadness aversion ($\beta > 0$) would induce one to choose the equal split E over the unequal split U. Hence, for a risk-averse individual who plays E, we may obtain a larger estimated β under risk neutrality than under CRRA preferences.

The ICL criterion allows comparison of the fit of the CRRA and risk-neutral models, respectively (see Tables 4 and 5). For any given number of types, the CRRA model has a

[27] Table A.6 shows that the assignment of subjects to types for the risk-neutral two-types (panel B) model, is very similar to when we impose $r_k = 1$. For the three-types models (panel C), some who are classified as "Type 2" with $r_k = 1$ are classified as "Type 1" under risk-neutrality and vice versa.

Table 5: Estimates at the aggregate level (logarithmic utility)

	1 type	2 types		3 types		
	Rep. agent	Type 1	Type 2	Type 1	Type 2	Type 3
α_k	0.13	0.05	0.24	0.12	−0.03	0.24
	(0.02)	(0.03)	(0.04)	(0.06)	(0.05)	(0.04)
β_k	−0.01	0.09	−0.29	0.22	−0.06	−0.29
	(0.03)	(0.03)	(0.07)	(0.04)	(0.07)	(0.08)
κ_k	0.20	0.23	0.17	0.24	0.21	0.17
	(0.01)	(0.02)	(0.02)	(0.06)	(0.05)	(0.02)
λ_k	0.24	0.27	0.16	0.20	0.31	0.15
	(0.02)	(0.02)	(0.02)	(0.03)	(0.05)	(0.01)
ϕ_k	1.00	0.59	0.41	0.29	0.30	0.41
	(-)	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)
$\ln L$	-2356.8	-2165.6			-2140.0	
$EN(\boldsymbol{\tau})$	0.00	5.43			17.02	
ICL	4732.5	4379.1			4363.1	
NEC	-	0.028			0.078	

Notes: Bootstrapped standard errors in parentheses. Table based on our 'core sample' of 112 subjects. In these estimations, we impose $r_k = 1$ (i.e. logarithmic utility) for all types.

considerably lower ICL score than the risk-neutral model. For the three-types model, for example, the ICL score under the CRRA assumption is quite a bit lower than under risk neutrality (4363.1 versus 4531.9), showing that the CRRA model considerably improves the fit over the risk-neutrality model.

5.2 Rational expectations

So far, we assumed that people maximize expected utility given their (reported) subjective expectations. In Appendix A4.2, we estimate the preference parameters taking rational expectations instead. At the individual level, the estimated individual preference parameters under subjective and rational expectations are significantly correlated. At the aggregate level, the finite mixture models under rational expectations (see Table A.12 in Appendix A4.2) are qualitatively similar to those under subjective expectations for most types, although we also observe some differences for a part of the population. In particu-

lar, we observe that Type 2 in the two-types model, and Type 3 in the three-types model, now display spite ($\alpha_k > 0, \beta_k < 0$) with strong morality ($\kappa_k > 0$). This contrasts with the estimates under subjective expectations where these types combined behindness aversion with milder morality.[28] Given a number of types, the ICL scores under rational expectations are higher than under subjective expectations, indicating a worse fit under rational expectations.

5.3 Game protocol type specific noise parameters

In the main analyses, we assume that the noise parameter λ is the same across game protocols. However, it could be that the error variance, and hence the noise parameter, is greater in certain type of game protocols. In Table A.13 in Appendix A4.3 we show finite mixture models where we allow for different noise parameters λ for each game protocol type (SPD, TG, UG). The estimates of the preference parameters of the 1-type and 2-types model are nearly identical to those in Table 4. For the 3-types model we observe some minor differences, but still the types are qualitatively similar. In particular, all the estimates of κ are significant, and in the same ballpark as in the main analysis.

6 The value added of Kantian morality

In this section, we extend the pre-registered analysis to also include the reciprocity parameter δ_i of the utility function in (1), and we benchmark the added value of the Kantian morality parameter κ_i against the three other parameters, α_i, β_i, and δ_i.

[28] Table A.6 (panels D and E) shows that the assignment of subjects to types is similar under subjective and rational expectations.

6.1 Aggregate estimations

Table 6 shows the estimates of the finite mixture estimates for the model allowing for distributional preferences (α_k, β_k), Kantian morality (κ_k) and reciprocity (δ_k). Including the reciprocity parameter δ_k has limited effects on the parameter estimates compared to the pre-registered models in Table 4. For most types, the parameter estimates of α_k, β_k, and κ_k are nearly identical and the estimate of δ_k is not significantly different from zero. Only for those subjects classified as Type 2 in the two-types model and Type 3 in the three-types model, we observe that the α_k estimates larger than those in Table 4, while the δ_k estimates are negative. For nearly all types, the estimates of β_k and κ_k are nearly identical when comparing Tables 4 and 6, although for Type 2 in the three-types model, κ_k is smaller and not significantly different from zero.[29]

To study the value-added of Kantian morality, we compare one-, two-, and three-types models allowing for combinations of distributional preferences (α, β), Kantian morality (κ) and reciprocity (δ). Tables 4 and 6 showed the results for models allowing for (α, β, κ) and $(\alpha, \beta, \kappa, \delta)$ respectively. In Tables A.8 and A.9 in Appendix A1 we report the results for models allowing for only distributional preferences (α, β) and distributional preferences in combination with reciprocity (α, β, δ) respectively. The left panel of Figure 6 shows the ICL scores for these models. Two things become clear from this figure. First, as lower ICL scores indicate a more preferred model, all multi-types models strongly outperform the one-type (representative agent) models. Second, for any given number of types, models that allow for Kantian morality give substantially lower ICL scores than models without Kantian morality, indicating that finite mixture estimates that include the parameter κ_i provide a better fit. The right panel shows a similar figure, but now assuming logarithmic utility ($r_k = 1$) instead of risk neutrality. Again, the multi-types models strongly outperform the representative agent models. Moreover, in line with the observations in section

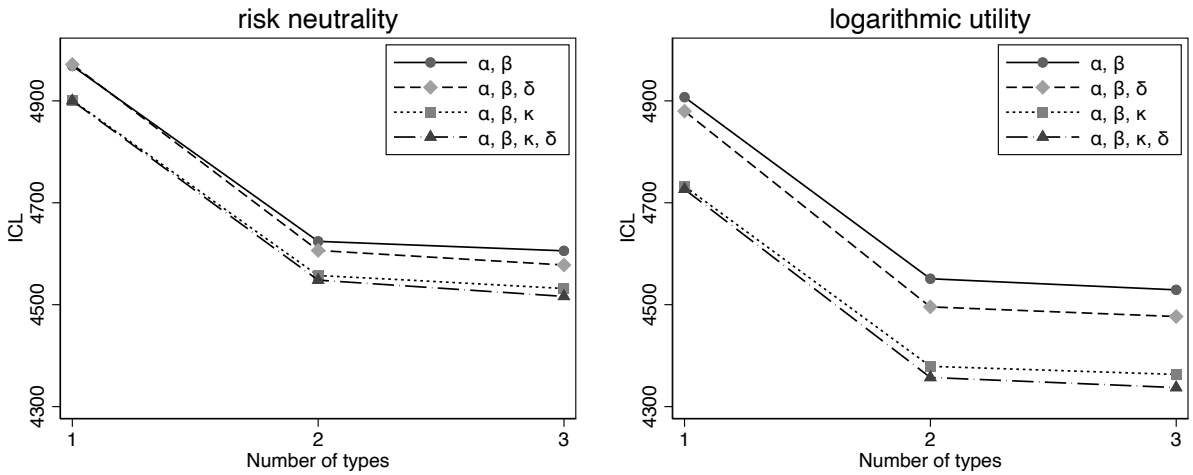
[29] Table A.6 (panels F and G) shows that the assignment of subjects to types is similar with and without reciprocity, although for the three-types models (panel G), some who are classified as "Type 1" without reciprocity are classified as "Type 2" with reciprocity.

Table 6: Estimates at the aggregate level (distributional, morality, and reciprocity)

	1 type	2 types		3 types		
	Rep. agent	Type 1	Type 2	Type 1	Type 2	Type 3
α_k	0.18	0.09	0.31	0.06	0.09	0.31
	(0.02)	(0.03)	(0.07)	(0.04)	(0.05)	(0.09)
β_k	0.24	0.35	0.02	0.18	0.51	0.02
	(0.03)	(0.05)	(0.05)	(0.06)	(0.04)	(0.04)
κ_k	0.10	0.11	0.11	0.14	0.05	0.11
	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
δ_k	−0.04	0.05	−0.16	0.10	0.01	−0.17
	(0.02)	(0.04)	(0.06)	(0.08)	(0.04)	(0.07)
λ_k	7.24	8.39	4.74	8.92	6.44	4.56
	(0.47)	(0.70)	(0.57)	(1.45)	(0.87)	(0.56)
ϕ_k	1.00	0.57	0.43	0.31	0.29	0.40
	(-)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)
$\ln L$	-2438.3	-2244.5			-2210.1	
$EN(\boldsymbol{\tau})$	0.00	7.37			15.81	
ICL	4900.3	4548.2			4516.3	
NEC	-	0.038			0.069	

Notes: Standard errors in parentheses. Based on our 'core sample' of 112 subjects, Table A.7 in Appendix A1 shows estimates based on all 136 subjects. For all types, we impose $r_k = 0$ (risk neutrality).

Figure 6: ICL scores



Notes: ICL scores of different finite mixture models. Lower ICL scores indicate a more preferred model. The left panel assumes risk neutrality ($r_k = 0$); the right panel assumes logarithmic utility ($r_k = 1$. Figure based on our 'core sample' of 112 subjects.

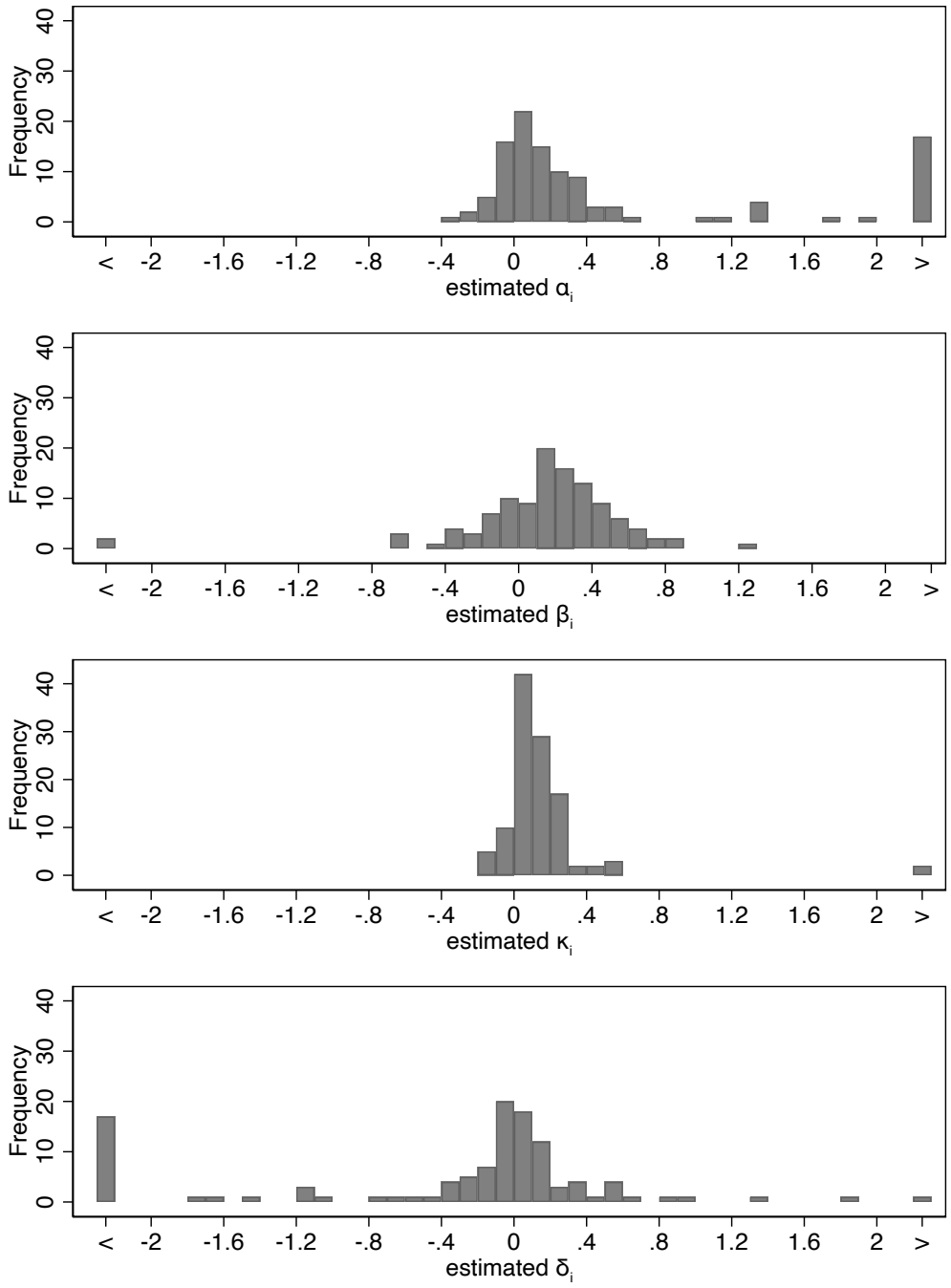
5, allowing for CRRA preferences strongly improves the fit of the models, indicated by the lower ICL scores in the right panel. Also under logarithmic utility, we find that the models including the Kantian morality parameter κ, clearly outperform the models without κ.

6.2 Individual estimations

Figure 7 shows the individual parameter estimates when allowing for distributional preferences (α_i, β_i), Kantian morality (κ_i) and reciprocity (δ_i). As in the pre-registered model without reciprocity, most individual estimates of α_i, β_i, and κ_i are positive. For the reciprocity parameter δ_i, we observe considerable heterogeneity, and both negative and positive estimates. Table A.10 in Appendix A1 shows summary statistics.

To study the value-added of the different preference parameters, we consider all models that are nested in (1) and apply standard information criteria. We use both the Bayesian information criterion (BIC) and Akaike's Information Criterion (AIC), each of

Figure 7: Distributions of individual parameter estimates (distributional, morality, and reciprocity)



Note: All estimates of α_i, β_i, κ_i, δ_i larger than 2 in absolute value are grouped in bins ("<" and ">") at the extremes of the horizontal axis. Figure based on our 'core sample' of 112 subjects. Figure A.3 in Appendix A1 shows a figure based on all 136 subjects. For all subjects, we assume risk neutrality ($r_i = 0$).

Table 7: Best individual fit

	BIC		AIC	
Parameters	Frequency	Percentage	Frequency	Percentage
$\alpha_i, \beta_i, \kappa_i, \delta_i$	0	0.0	0	0.0
$\alpha_i, \beta_i, \kappa_i$	1	0.9	3	2.7
$\alpha_i, \beta_i, \delta_i$	5	4.5	9	8.0
$\alpha_i, \kappa_i, \delta_i$	2	1.8	4	3.6
$\beta_i, \kappa_i, \delta_i$	0	0.0	3	2.7
α_i, β_i	5	4.5	5	4.5
α_i, κ_i	6	5.4	9	8.0
α_i, δ_i	5	4.5	5	4.5
β_i, κ_i	4	3.6	3	2.7
β_i, δ_i	3	2.7	4	3.6
κ_i, δ_i	4	3.6	3	2.7
α_i	4	3.6	2	1.8
β_i	38	33.9	33	29.5
κ_i	5	4.5	6	5.4
δ_i	0	0.0	1	0.9
-	30	26.8	22	19.6
Selected model includes:				
Parameter	Frequency	Percentage	Frequency	Percentage
α_i	28	25.0	37	33.0
β_i	56	50.0	60	53.6
κ_i	22	19.6	31	27.7
δ_i	19	17.0	29	25.9

Notes: Entries in the top panel indicate the number of subjects for whom the specific model provides the lowest BIC or AIC score respectively. Entries in the bottom panel summarize how frequently a parameter was included in the the model the lowest BIC or AIC score respectively. Table based on our 'core sample' of 112 subjects. For all subjects, we assume risk neutrality ($r_i = 0$).

which is based on the log-likelihoods and adds a penalty for each parameter. The lower score, the better fit. More precisely, the criteria are:

$$BIC = -2\ln(L) + d\ln(18), \tag{17}$$

and

$$AIC = -2\ln(L) + 2d, \tag{18}$$

where $\ln(18)$ in (17) comes from the 18 observations per subject. Since $\ln 18 \approx 2.89 > 2$, BIC gives a heavier penalty per parameter than AIC.

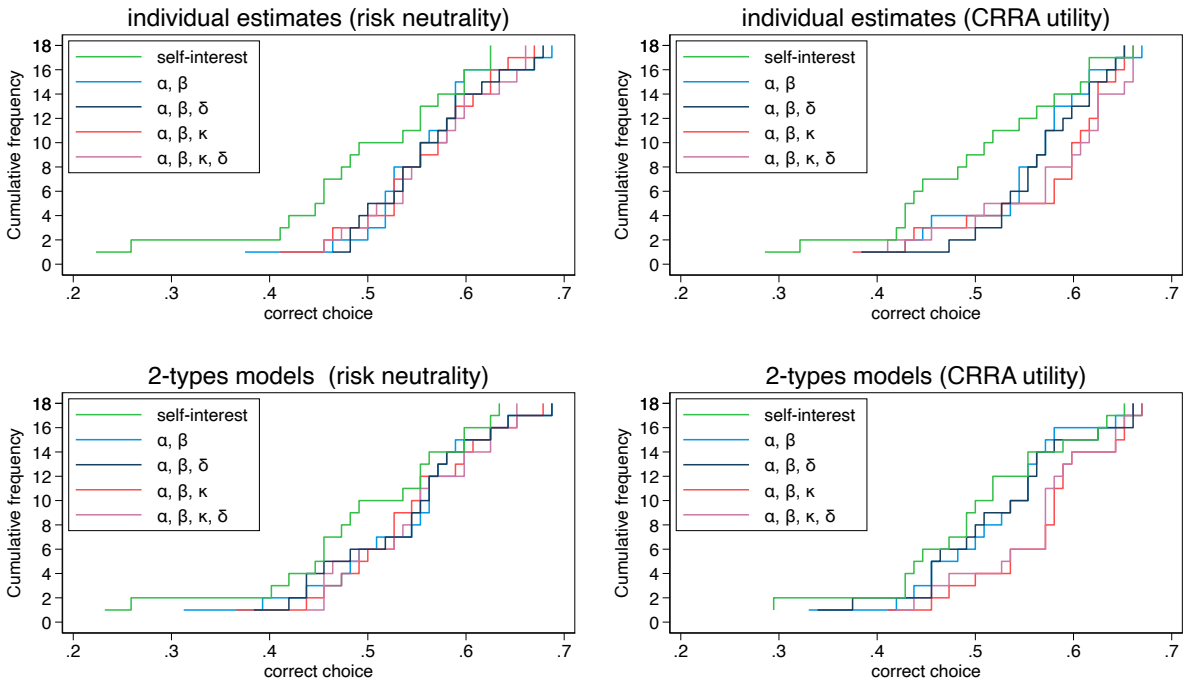
Table 7 shows the results. The left side of the table shows which model provides the best fit according to BIC. For 30 subjects (26.8%) pure self-interest ($\alpha_i = \beta_i = \kappa_i = \delta_i = 0$) has the lowest BIC score. This contrasts with the aggregate estimates (Table 6), where no purely self-interested type emerges. This difference may be the result of the relatively small number of observations for each individual estimation, giving less power to reject self-interest at the individual level. For the remaining 82 subjects, some combinations of social preferences and/or moral concerns improve the model's fit. In sum, for 22 subjects (19.6%), the model with the lowest BIC score includes κ_i. In comparison, α_i, β_i and δ_i are included in the model with the lowest BIC score for 28 subjects (25.0%), 56 subjects (50.0%), and 19 subjects (17.0%), respectively. In particular β_i (aheadness aversion) plays a big role and improves the fit for half the subjects, while the value-added of each of the other three preference parameters is roughly in the same ballpark. The right side of Table 7 shows the results from the same exercise, but now applied to AIC. Then the best-fitting model at the individual level includes the parameter κ_i for 31 subjects (or 27.7%). Again, a smaller number of subjects than for β_i (60 subjects, or 53.6%), but a similar number of subjects as for α_i (37 subjects, or 33.0%) and also δ_i (29 subjects, or 25.9%).

6.3 Out-of-sample predictions

So far, we evaluated the performance of different models based on information criteria. As an alternative, we consider the predictive accuracy of different models by conducting out-of-sample predictions. For each of the 18 game protocols, we estimate parameters based on the other 17 game protocols, and use the estimates to predict the choice for the one omitted game protocol. We conduct these analyses both at the individual level and the aggregate level.

Figure 8 illustrates the results, by comparing the predictive accuracy of models allowing for distributional preferences (α, β), distributional preferences in combination with either reciprocity (α, β, δ) or Kantian morality (α, β, κ) or both $(\alpha, \beta, \kappa, \delta)$. The left panels

Figure 8: Accuracy of out-of-sample predictions



Notes: Accuracy of out-of-sample predictions, based on individual estimates (top panels) and finite mixture models with two-types (bottom panels). The plots on the left assume risk neutrality ($r = 0$). The plots on the right allow for CRRA utility. For the individual estimates with CRRA utility, we use the lottery choices to impose risk attitudes. For the finite mixture models, we impose logarithmic utility ($r_k = 1$) for all types. Plots show cumulative frequency plots for the average fraction of correctly predicted choices per game protocol. Figure based on our 'core sample' of 112 subjects.

of Figure 8 assume risk neutrality, while the right panels of Figure 8 allow for CRRA preferences. The top left panel of Figure 8 compares the predictive accuracy based on individual estimates, under risk neutrality. All models clearly outperform random choice (which would lead to 20.8% accurate predictions in expectation). All models allowing for distributional preferences perform much better than when assuming self-interest, but the differences in predictive accuracy between these models are small. On average, The (α, β, κ)-model on average predicts 55.5% of choices correctly, somewhat more than the (α, β) model which predicts 55.1% of choices correctly, and slightly less than the (α, β, δ) and (α, β, κ, δ) models, which give 55.9% and 56.1% average accuracy, respectively. All models allowing for distributional preferences, reciprocity and/or Kantian morality perform much better than when assuming self-interest, which gives 48.8% average accuracy.

The bottom left panel of Figure 8 shows the predictive accuracy of finite mixture models assuming two types under risk neutrality. As for the individual estimates, the two-types model with distributional preferences, reciprocity and/or Kantian morality outperform self-interest, but the differences between these models are modest. The (α, β, κ)-model predicts 53.9% of choices correctly, which is better than the two-types (α, β)-model which gives 53.2% accuracy. The value-added of reciprocity is somewhat lower for the two-types models. The reciprocity model (α, β, δ) achieves 53.4% accuracy, while the 'full' (α, β, κ, δ) model gives 54.4% average accuracy. Note that the predictive accuracy of the two-types models are not far from the respective models with individual estimates.[30] This provides further evidence that the two-types model effectively captures the heterogeneity in preferences.

The right panels of Figure 8 show out out-of-sample predictions under CRRA preferences. For the individual estimations, we again base the risk parameters r_i on the lottery choices, while for the finite mixture estimates we impose logarithmic utility ($r_k = 1$).

[30]When allowing for Kantian morality (α, β, κ), a model with a representative agent (1 type) performs worse (47.9% accuracy) than the two-types model, and a model with three-types performs even better (54.9%) than the two-types model.

Under CRRA preferences, models allowing for Kantian morality clearly outperform the other models in terms of predictive accuracy. With individual estimates, the (α, β, κ) model has an accuracy of 57.0%, whereas the model with only distributional preferences (α, β) predicts 55.2% correctly. For the two-types model, the difference is more pronounced. With only distributional preferences (α, β) accuracy is 51.9%, which increases to 56.6% when allowing for distributional preferences and Kantian morality (α, β, κ). Under CRRA preferences, the value-added of reciprocity is limited. At the individual level, the (α, β, δ) and $(\alpha, \beta, \delta, \kappa)$ models have an accuracy of 56.2% and 57.2% respectively. For the two-types models, allowing for reciprocity results in 51.9% accuracy for the (α, β, δ) model and 56.0% for the $(\alpha, \beta, \delta, \kappa)$ model.

In sum, under risk neutrality the value-added of Kantian morality and reciprocity is limited in the out-of-sample predictions. This contrasts with the improved within-sample fit when allowing for Kantian morality that we observed in Figure 6. Under CRRA preferences, we find that Kantian morality improves both predictive accuracy in the out-of-sample exercise and the within-sample fit of the models.

7 Concluding discussion

In this paper, we report results from a laboratory experiment designed to evaluate the explanatory power of Kantian morality in standard strategic interactions. To distinguish Kantian morality from other social concerns, we posit a general utility function that nests several much studied preference classes, such as pure self-interest, altruism, spite, inequity aversion, and reciprocity, and of course Kantian morality. We structurally estimate the preference parameters of this utility function controlling for the beliefs about opponent's play. We obtain both individual and aggregate estimates, where the latter consists of estimating the parameters for a representative agent, as well as identifying a small number of endogenously determined "preference types".

The individual estimates suggest substantial heterogeneity. This heterogeneity limits the usefulness of a representative agent approach. However, we find that the subjects' behaviors are well captured by models with two or three preference types. Assuming risk neutrality, the two-types model suggests that roughly 60% of subjects display a combination of inequity aversion with Kantian morality, and the remaining share a combination of Kantian morality and behindness aversion. Quite remarkably, however, all the preference types—both the representative agent and the preference types within the two-types and the three-types model—have an estimated Kantian morality parameter κ of around 0.1. The finding that all types have a positive κ also holds when we allow for reciprocity and/or risk aversion.

Compared with other experimental studies with structural preference estimations, our results agree with those of Bruhin et al. (2019) in that their behavioral data is largely consistent with there being a small number of "preference types". Our findings further agree with Bruhin et al. (2019) in that they do not either find evidence that the purely selfish *Homo oeconomicus* explains their behavioral data. A more detailed comparison is more involved, since their experimental design differs from ours, and they do not include Kantian morality. Our results further agree broadly with those in the horse race study by Miettinen et al. (2020), although our richer data set allows us to capture the complex combination of subjects' motives that their study cannot address.

Our experimental design was motivated by findings in the theoretical literature that investigates the evolutionary foundations of preferences in strategic interactions (see Alger & Weibull, 2019, for a recent survey). Interestingly, our findings are in line with the theoretical prediction that evolution by natural selection favors preferences that combine not only self-interest and Kantian morality, but also either altruism or spite, when preferences are expressed at the level of material payoffs (Alger et al., 2020).[31] Indeed, our finite

[31]This result does not contradict that of Alger and Weibull (2013), according to which evolution by natural selection favors a convex combination between self-interest and Kantian morality. Indeed, Alger et al. (2020) confirm in their model that such preferences are indeed favored by evolution when it is own and other's reproductive success that appear as arguments in the utility function, rather than (trivial) material

mixture estimates show that essentially all types combine self-interest, Kantian morality, and some concern for the other's payoff. However, our analysis also reveals an intriguing finding. The estimated attitude towards being ahead materially is qualitatively different in the estimates that assume risk neutrality and those that assume risk aversion: while all types are either indifferent to other's payoff or altruistic towards the other when ahead under risk neutrality, a sizeable share of the subjects are classified as being spiteful when ahead under risk aversion. This result clearly begs for further research.

Our posited utility function is richer than most examined before: in addition to Kantian morality, it allows for altruism, spite, inequity aversion, and reciprocity. As is the case for all other similar studies, it could be, however, that other motivations not included in the posited utility function drive (part) of the behavior. For future research, it would be interesting to study the value added of Kantian morality compared to other motivations like guilt aversion and image concerns. It would further be interesting to examine whether results similar to ours also obtain in a representative sample, along the lines of the studies by Bellemare et al. (2008) and Cettolin and Suetens (2018). While evolutionary theory suggests that the qualitative nature of preferences guiding behavior in strategic interactions should be similar across the world, certain differences between populations may be expected to influence the relative importance of self-interest, social concerns, and Kantian morality. In particular, since evolutionary theory suggests that migration patterns and the involvement in inter-group conflict are expected to impact preferences guiding behavior in strategic interactions (Alger et al., 2020; Choi & Bowles, 2007), this theory delivers testable predictions that may help explain cross-cultural differences (Falk et al., 2018) and also perhaps differences between men and women (Croson & Gneezy, 2009). Finally, it would be interesting to investigate more precisely whether Kantian morality can help explain the formation of social norms (Bicchieri, 2005; Krupka & Weber, 2013; Elster, 1989), as well as the documented enhancement of pro-social be-

payoffs.

haviors triggered by role uncertainty (Iriberri & Rey-Biel, 2011). Related to the last issue, our experimental design is adapted to detect *Homo moralis* preferences in *ex ante* symmetric situations, because the current theoretical models define these preferences in such settings; future work may reveal fruitful ways to formalize, and also test, a similar form of Kantian morality in asymmetric settings.

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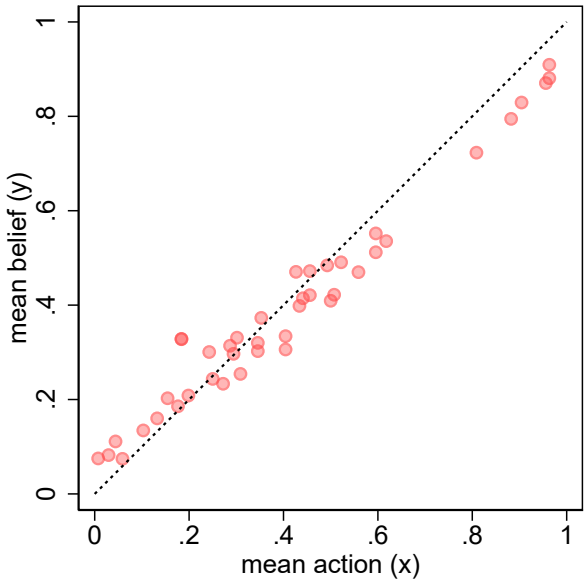
Appendices (For Online Publication)

Appendix A1 Additional tables and figures

Figure A.1: Correlations between mean actions and beliefs



Note: Each dot represents the mean action x and mean stated belief y for each of the actions (listed in Table 1). Means are taken across all 136 subjects.

Table A.1: Lottery choices

	Outcomes				
Lottery	A	B	Frequency	Percentage	r_i
Sessions 2-8					
1	18	18	50	43.9%	1.61
2	22	15	24	21.1%	1.00
3	26	12	18	15.8%	0.39
4	30	9	3	2.6%	0.25
5	34	6	8	7.0%	0.08
6	37	2	11	9.7%	-0.09
Session 1					
1	18	18	5	22.7%	4.71
2	22	16	3	13.6%	2.95
3	26	14	6	27.3%	1.19
4	30	12	4	18.2%	0.77
5	34	10	2	9.1%	0.32
6	40	4	2	9.1%	-0.13

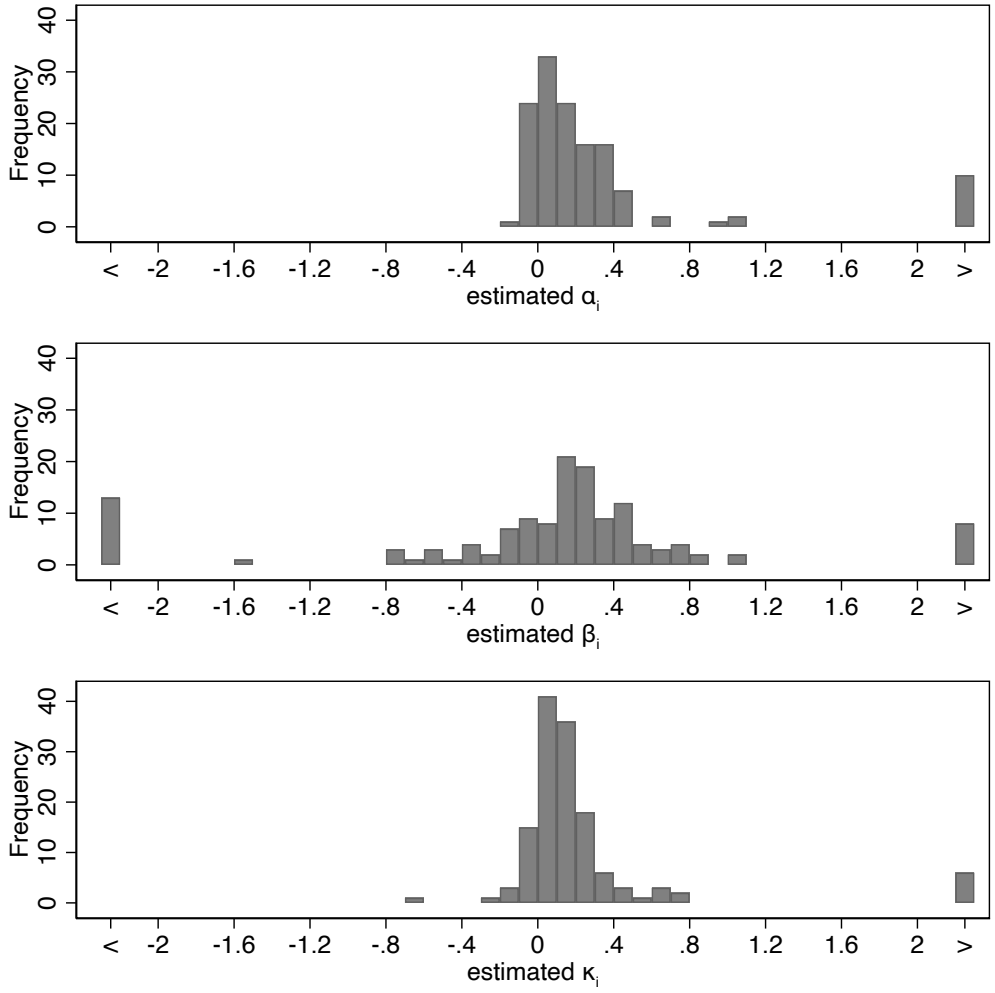
Notes: Lottery choices in the Eckel and Grossman (2002) risk elicitation task. 'Outcomes' are the payoffs denoted in "points", see Appendix A7 for the instructions. The final column lists the implied r_i parameters for each lottery choice. Note that after the first session, we slightly adjusted the outcomes to better estimate r_i. Table based on all 136 subjects.

Table A.2: Individual parameter estimates (all subjects)

Parameter	Median	Mean	S.D.	Min	Max
α_i	0.14	2084.23	12038.55	−0.19	78758.51
β_i	0.18	−899.34	7167.41	−69307.41	9153.14
κ_i	0.11	1097.68	6591.74	−0.68	50309.22

Notes: Table based on estimates from all 136 subjects. For all subjects, we assume risk neutrality ($r_i = 0$).

Figure A.2: Distributions of individual parameter estimates (all subjects)



Note: All estimates of α_i, β_i and κ_i larger than 2 in absolute value are grouped in bins ("<" and ">") at the extremes of the horizontal axis. Figure based on all 136 subjects. For all subjects, we assume risk neutrality ($r_i = 0$).

Table A.3: Estimates at the aggregate level (all subjects)

	1 type	2 types		3 types		
	Rep. agent	Type 1	Type 2	Type 1	Type 2	Type 3
α_k	0.18	0.15	0.17	0.21	0.03	0.17
	(0.01)	(0.02)	(0.02)	(0.03)	(0.04)	(0.02)
β_k	0.25	0.37	−0.02	0.26	0.52	−0.03
	(0.02)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)
κ_k	0.11	0.12	0.09	0.12	0.16	0.09
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.02)
λ_k	7.89	9.68	3.74	10.40	6.52	3.59
	(0.46)	(0.51)	(0.51)	(0.96)	(0.68)	(0.29)
ϕ_k	1.00	0.63	0.37	0.49	0.17	0.34
	(-)	(0.06)	(0.06)	(0.06)	(0.04)	(0.04)
$\ln L$	-3026.9	-2762.6			-2706.6	
$EN(\boldsymbol{\tau})$	0.00	6.06			13.64	
ICL	6073.4	5575.5			5495.6	
NEC	-	0.023			0.043	

Notes: Standard errors in parentheses. Table based on all 136 subjects. For all types, we assume risk neutrality ($r_k = 0$).

Table A.4: The 4-types model

	Type 1	Type 2	Type 3	Type 4
α_k	0.17	0.16	0.02	0.16
	(0.03)	(0.03)	(0.03)	(0.06)
β_k	−0.01	0.17	0.46	0.51
	(0.04)	(0.05)	(0.06)	(0.08)
κ_k	0.09	0.12	0.15	0.04
	(0.02)	(0.01)	(0.05)	(0.03)
λ_k	3.63	8.66	8.56	4.67
	(0.29)	(1.54)	(1.12)	(0.61)
ϕ_k	0.34	0.35	0.19	0.12
	(0.05)	(0.07)	(0.06)	(0.05)
$\ln L$		-2212.6		
$EN(\boldsymbol{\tau})$		23.45		
ICL		4538.3		
NEC		0.103		

Notes: Standard errors in parentheses. For all types, we impose $r_k = 0$ (risk neutrality). Estimation results from models with 1, 2 and 3 types can be found in Table 4. Based on our 'core sample' of 112 subjects.

Table A.5: Strategies by type

	1 type	2 types		3 types		
	Rep. agent	Type 1	Type 2	Type 1	Type 2	Type 3
Sequential Prisoner's Dilemmas						
C,C,C	2%	3%	0%	2%	5%	0%
C,C,D	21%	30%	5%	20%	61%	5%
C,D,C	0%	1%	0%	1%	0%	0%
C,D,D	9%	10%	7%	12%	6%	7%
D,C,C	1%	2%	0%	2%	5%	0%
D,C,D	7%	10%	2%	11%	8%	2%
D,D,C	3%	3%	2%	2%	6%	2%
D,D,D	57%	40%	84%	51%	10%	84%
Trust Games						
I,G	28%	43%	5%	31%	78%	4%
I,K	16%	21%	9%	23%	11%	10%
N,G	4%	6%	3%	8%	1%	2%
N,K	51%	30%	83%	39%	10%	85%
Ultimatum Games						
E,A	42%	56%	21%	54%	59%	20%
E,F	8%	10%	3%	10%	11%	3%
U,A	50%	34%	75%	36%	30%	77%
U,F	0%	0%	0%	0%	0%	0%

Notes: Relative frequencies (in %) of chosen strategies based on the 1, 2, and three-types models reported in Table 4. Subjects are assigned a type based on the type posterior probability $\tau_{i,k}$ (that subject i belongs to type k, see eq. (11)).

Table A.6: Transitions between types

Panel A: 2 types and 3 types (risk neutral)

	2 types	
3 types	Type 1	Type 2
Type 1	52	3
Type 2	17	0
Type 3	0	40

Panel B: 2 types, ln and risk neutral

	2 types ($r = 1$)	
2 types ($r = 0$)	Type 1	Type 2
Type 1	63	6
Type 2	2	41

Panel C: 3 types, ln and risk neutral

	3 types ($r = 1$)		
3 types ($r = 0$)	Type 1	Type 2	Type 3
Type 1	19	28	8
Type 2	13	4	0
Type 3	0	2	38

Panel D: 2 types, subjective and rational expectations (ln)

	2 types (rational exp.)	
2 types (subj. exp.)	Type 1	Type 2
Type 1	59	10
Type 2	4	39

Panel E: 3 types, subjective and rational expectations (ln)

	3 types (rational exp.)		
3 types (subj. exp.)	Type 1	Type 2	Type 3
Type 1	35	10	10
Type 2	3	14	0
Type 3	3	0	37

Panel F: 2 types, with and without reciprocity (δ)

	2 types ($\alpha, \beta, \kappa, \delta$)	
2 types (α, β, κ)	Type 1	Type 2
Type 1	64	5
Type 2	2	41

Panel G: 3 types, with and without reciprocity (δ)

	3 types ($\alpha, \beta, \kappa, \delta$)		
3 types (α, β, κ)	Type 1	Type 2	Type 3
Type 1	28	19	8
Type 2	4	13	0
Type 3	2	0	38

Notes: Each panel shows transition matrices between types in different finite mixture models. Subjects are assigned a type based on the posterior probability $\tau_{i,k}$ (that subject i belongs to type k, see eq. (11)).

Table A.7: Estimates at the aggregate level (distributional, morality, and reciprocity; all subjects)

	1 type	2 types		3 types		
	Rep. agent	Type 1	Type 2	Type 1	Type 2	Type 3
α_k	0.20	0.12	0.25	0.19	0.02	0.23
	(0.02)	(0.03)	(0.07)	(0.06)	(0.05)	(0.05)
β_k	0.24	0.36	−0.03	0.24	0.54	−0.03
	(0.02)	(0.04)	(0.05)	(0.05)	(0.17)	(0.04)
κ_k	0.11	0.11	0.10	0.12	0.15	0.09
	(0.01)	(0.01)	(0.02)	(0.01)	(0.04)	(0.02)
δ_k	−0.04	0.04	−0.12	0.03	0.03	−0.11
	(0.02)	(0.03)	(0.05)	(0.05)	(0.10)	(0.04)
λ_k	7.96	9.32	4.10	10.28	7.16	3.73
	(0.46)	(0.76)	(0.65)	(1.03)	(1.57)	(0.35)
ϕ_k	1.00	0.63	0.37	0.48	0.18	0.34
	(-)	(0.06)	(0.06)	(0.06)	(0.06)	(0.04)
$\ln L$	-3023.6	-2750.8			-2695.0	
$EN(\boldsymbol{\tau})$	0.00	6.56			13.89	
ICL	6071.8	5562.1			4587.4	
NEC	-	0.024			0.042	

Notes: Standard errors in parentheses. Based on all 136 subjects. For all types, we impose $r_k = 0$ (risk neutrality).

Table A.8: Estimates at the aggregate level (distributional preferences)

	1 type	2 types		3 types		
	Rep. agent	Type 1	Type 2	Type 1	Type 2	Type 3
α_k	0.06	0.03	0.06	0.03	0.03	0.06
	(0.01)	(0.02)	(0.01)	(0.05)	(0.04)	(0.01)
β_k	0.32	0.44	0.08	0.28	0.57	0.08
	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
λ_k	6.98	8.09	3.75	8.23	6.84	3.32
	(0.46)	(0.68)	(0.35)	(2.16)	(0.95)	(0.32)
ϕ_k	1.00	0.61	0.39	0.37	0.29	0.34
	(-)	(0.07)	(0.07)	(0.09)	(0.06)	(0.06)
$\ln L$	-2477.2	-2292.5			-2267.1	
$EN(\boldsymbol{\tau})$	0.00	6.38			19.66	
ICL	4968.6	4624.4			4605.7	
NEC	-	0.035			0.094	

Notes: Standard errors in parentheses. Based on our 'core sample' of 112 subjects. For all types, we impose $r_k = 0$ (risk neutrality).

Table A.9: Estimates at the aggregate level (distributional, reciprocity)

	1 type	2 types		3 types		
	Rep. agent	Type 1	Type 2	Type 1	Type 2	Type 3
α_k	0.07	0.01	0.13	−0.01	0.02	0.14
	(0.02)	(0.03)	(0.05)	(0.09)	(0.06)	(0.05)
β_k	0.32	0.42	0.07	0.27	0.56	0.07
	(0.02)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
δ_k	−0.02	0.06	−0.12	0.06	0.04	−0.13
	(0.02)	(0.03)	(0.05)	(0.10)	(0.05)	(0.05)
λ_k	7.00	8.07	3.58	8.18	6.83	3.58
	(0.46)	(0.66)	(0.49)	(1.62)	(0.96)	(0.44)
ϕ_k	1.00	0.65	0.35	0.35	0.30	0.35
	(-)	(0.07)	(0.07)	(0.08)	(0.06)	(0.05)
$\ln L$	-2476.4	-2279.5			-2247.4	
$EN(\boldsymbol{\tau})$	0.00	4.92			17.01	
ICL	4971.6	4606.4			4577.9	
NEC	-	0.025			0.074	

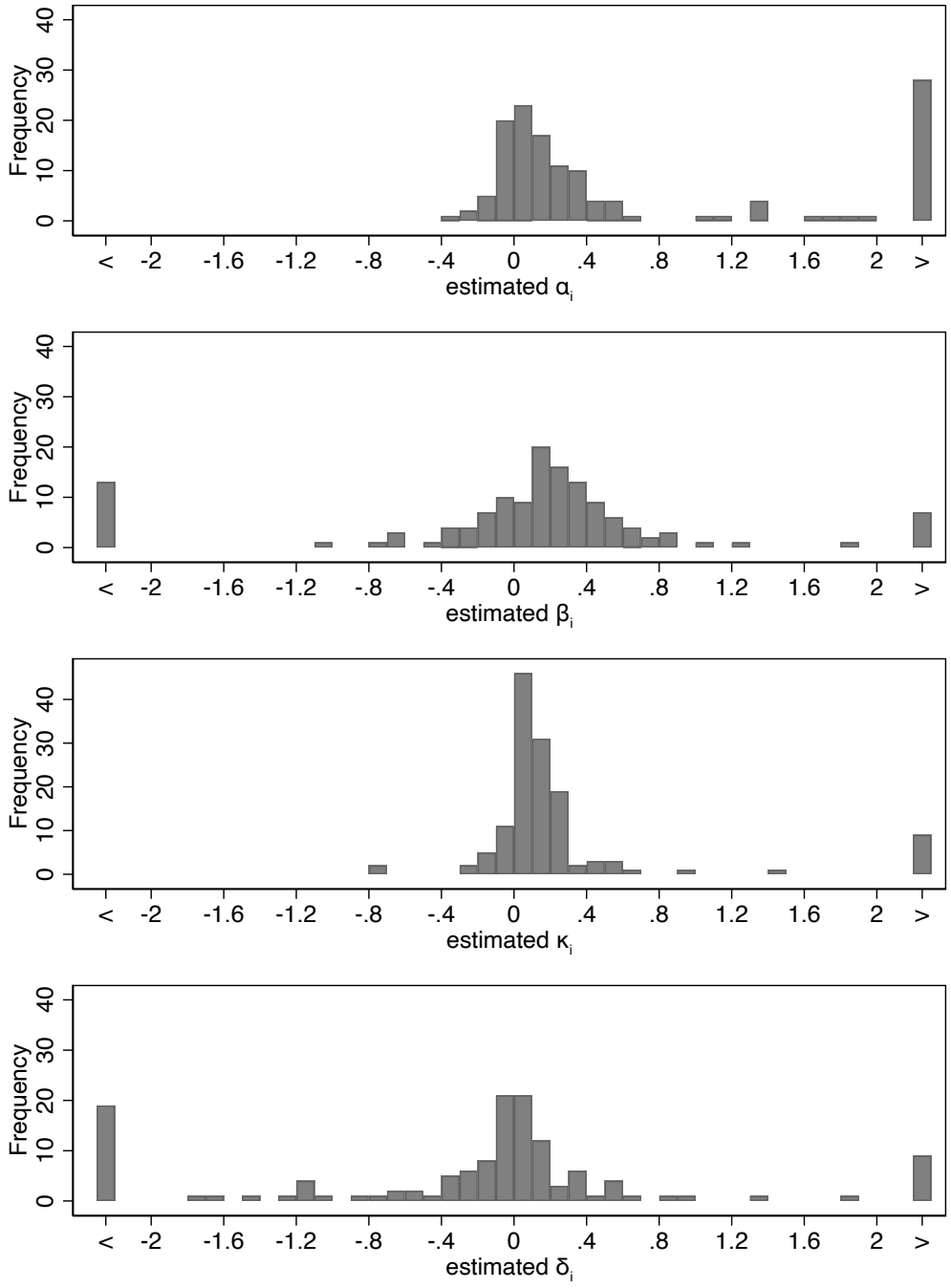
Notes: Standard errors in parentheses. Based on our 'core sample' of 112 subjects. For all types, we impose $r_k = 0$ (risk neutrality).

Table A.10: Individual parameter estimates (incl. reciprocity)

Parameter	Median	Mean	S.D.	Min	Max
α_i	0.16	1.91	9.10	−0.39	82.29
β_i	0.20	−0.15	2.90	−29.44	1.21
κ_i	0.10	0.22	0.87	−0.17	8.88
δ_i	−0.03	−1.59	8.73	−82.22	3.49

Notes: Table based on our 'core sample' of 112 subjects. For all subjects, we assume risk neutrality ($r_i = 0$).

Figure A.3: Distributions of individual parameter estimates (distributional, morality, and reciprocity; all subjects)



Note: All estimates of α_i, β_i, κ_i and δ_i larger than 2 in absolute value are grouped in bins ("<" and ">") at the extremes of the horizontal axis. Figure based on all 136 subjects. For all subjects, we assume risk neutrality ($r_i = 0$).

Appendix A2 Distinguishing Kantian morality from social preferences

Here we write the full expected utility expressions of a subject i with a utility function as in (1) in each of the three game protocols. The objective is to show the qualitative difference between Kantian morality on the one hand (as captured by κ_i), and social preferences on the other hand (as captured by α_i, β_i, and δ_i).

Beginning with the Ultimatum Game protocol, as in Figure 1c, i obtains the following expected utility from using behavior strategy $x = (x_1, x_2)$ when he believes that the opponent will use behavior strategy $\hat{y} = (\hat{y}_1, \hat{y}_2)$ (the randomization factor $1/2$ has been omitted):

$$\begin{aligned} u_i(x,\hat{y}) &= (1-\kappa_i)[x_1 R + (1-x_1)\hat{y}_2 T + (1-x_1)(1-\hat{y}_2) S \\ &\quad + \hat{y}_1 R + (1-\hat{y}_1) x_2 P + (1-\hat{y}_1)(1-x_2) S] \\ &\quad - [(\alpha_i + \delta_i)(1-\hat{y}_1) x_2 + \beta_i (1-x_1)\hat{y}_2](T-P) \\ &\quad + \kappa_i [x_1 R + (1-x_1) x_2 T + (1-x_1)(1-x_2) S \\ &\quad + x_1 R + (1-x_1) x_2 P + (1-x_1)(1-x_2) S]. \end{aligned} \tag{19}$$

The partial derivatives with respect to x_1 and x_2 are thus:

$$\begin{aligned} \frac{\partial u_i(x,\hat{y})}{\partial x_1} &= (1-\kappa_i)[R - \hat{y}_2 T - (1-\hat{y}_2) S] + \beta_i \hat{y}_2 (T-P) \\ &\quad + \kappa_i [2(R-S) - x_2 (T+P-2S)] \end{aligned} \tag{20}$$

$$\frac{\partial u_i(x,\hat{y})}{\partial x_2} = (1-\kappa_i)(1-\hat{y}_1)(P-S) - (\alpha_i + \delta_i)(1-\hat{y}_1)(T-P) + \kappa_i (1-x_1)(T+P-2S). \tag{21}$$

Note that in this game protocol behindness aversion matters only following the unfair offer, in which case it is augmented by the reciprocity parameter. Hence, in the following discussion we will refer to the term $\alpha_i + \delta_i$ simply as behindness aversion. To see the two

key effects of Kantian morality mentioned in the main text, we compare an individual who is inequity averse but does not have a Kantian concern ($(\alpha_i + \delta_i)\beta_i > 0 = \kappa_i$) to one who has a Kantian concern but is not inequity averse ($\kappa_i > 0 = \alpha_i + \delta_i = \beta_i$). First, when considering the effect of his choice as a first-mover, x_1, the inequity-averse individual pays no attention to his choice as a second-mover, while the Kantian moralist does (i.e., x_2 shows up in the derivative in (20) if and only if $\kappa_i \neq 0$). Likewise, when considering the effect of his choice as a second-mover, x_2, the inequity-averse individual pays no attention to his choice as a first-mover, while the Kantian moralist does (i.e., x_1 appears in (21) if and only if $\kappa_i \neq 0$). Second, the expressions (20) and (21) show that beliefs about the opponent's play (information that we elicit from the subjects) matter less for a pure Kantian moralist than for a purely inequity averse individual. In the extreme case where $1 = \kappa_i > \alpha_i + \delta_i = \beta_i = 0$, the Kantian moralist chooses the strategy that would maximize the expected material payoff should both players choose it, irrespective of what (s)he believes the opponent will play.

In the Trust Game protocol (Figure 1b), a behavior strategy is a vector $x = (x_1, x_2) \in X = [0,1]^2$, where x_1 is the probability with which the player trusts the receiver, and x_2 the probability with which he honors trust (if the sender trusts him).[32] Then the expected utility (as defined in (1)) from playing $x = (x_1, x_2)$ against $y = (y_1, y_2)$ is (omitting the factor $1/2$):

$$\begin{aligned} u_i(x,y) \;=\; & (1-\kappa_i)[x_1[y_2R + (1-y_2)S] + (1-x_1)P] \\ & + (1-\kappa_i)[y_1[x_2R + (1-x_2)T] + (1-y_1)P] \\ & + \kappa_i\{x_1[x_2R + (1-x_2)S] + (1-x_1)P\} \\ & + \kappa_i\{x_1[x_2R + (1-x_2)T] + (1-x_1)P\} \\ & - [\alpha_i x_1(1-y_2) + \beta_i y_1(1-x_2)](T-S). \end{aligned} \tag{22}$$

[32] Since each player has only one decision node, the distinction between mixed and behavioral strategies is immaterial.

Note that in this game protocol the reciprocity parameter δ_i does not appear, since behindness aversion applies only if the first mover invested and the second mover does not give back, while in this game protocol we classify Not invest (N) as misbehavior. Hence, for a subject who believes that the opponent plays $\hat{y}$:

$$\frac{\partial u_i(x,\hat{y})}{\partial x_1} = (1-\kappa_i)[S-P+\hat{y}_2(R-S)] + \kappa_i[x_2(2R-S-T)+S+T-2P] - \alpha_i(1-\hat{y}_2)(T-S), \tag{23}$$

and

$$\frac{\partial u_i(x,\hat{y})}{\partial x_2} = (1-\kappa_i)\hat{y}_1(R-T) + \kappa_i x_1(2R-S-T) + \beta_i \hat{y}_1(T-S). \tag{24}$$

Again, the individual's own play as second mover, x_2, appears in the derivative for play as first mover, x_1, if and only if $\kappa_i \neq 0$ (see in (23)). Likewise, the individual's own play as first mover, x_1, appears in the derivative for play as second mover, x_2, if and only if $\kappa_i \neq 0$ (see in (24)).

We turn finally to the Sequential Prisoners' Dilemma game protocol (as in Figure 1a). As noted in the main text, Defection by the first mover is classified as misbehavior if and only if $2R > S+T$. To account for this in the expression below, let q be a dummy variable that takes the value 1 if $2R > S+T$ and 0 otherwise. The expected utility (as defined in (1)) from playing $x = (x_1, x_2, x_3)$ against $y = (y_1, y_2, y_3)$ is then (again omitting the factor $1/2$):

$$\begin{aligned} u_i(x,y) \;=\; & (1-\kappa_i)[x_1y_2R + x_1(1-y_2)S + (1-x_1)y_3T + (1-x_1)(1-y_3)P] \\ & + (1-\kappa_i)[y_1x_2R + y_1(1-x_2)T + (1-y_1)x_3S + (1-y_1)(1-x_3)P] \\ & + \kappa_i[x_1x_2R + x_1(1-x_2)S + (1-x_1)x_3T + (1-x_1)(1-x_3)P] \\ & + \kappa_i[x_1x_2R + x_1(1-x_2)T + (1-x_1)x_3S + (1-x_1)(1-x_3)P] \\ & - \alpha_i x_1(1-y_2)(T-S) - (\alpha_i + q\delta_i)(1-y_1)x_3(T-S) \\ & - \beta_i[(1-x_1)y_3 + y_1(1-x_2)](T-S). \end{aligned} \tag{25}$$

Hence, for a subject who believes that the opponent would play $\hat{y}$ one obtains:

$$\begin{aligned}\frac{\partial u_i(x,\hat{y})}{\partial x_1} &= (1-\kappa_i)[S-P+\hat{y}_2(R-S)-\hat{y}_3(T-P)] \\ &\quad +\kappa_i[x_2(2R-S-T)+(1-x_3)(S+T-2P)] \\ &\quad +\beta_i\hat{y}_3(T-S)-\alpha_i(1-\hat{y}_2)(T-S),\end{aligned} \tag{26}$$

$$\frac{\partial u_i(x,\hat{y})}{\partial x_2} = (1-\kappa_i)\hat{y}_1(R-T)+\kappa_i x_1(2R-S-T)+\beta_i\hat{y}_1(T-S), \tag{27}$$

and

$$\frac{\partial u_i(x,\hat{y})}{\partial x_3} = (1-\kappa_i)(1-\hat{y}_1)(S-P)+\kappa_i(1-x_1)(T+S-2P)-(\alpha_i+q\delta_i)(1-\hat{y}_1)(T-S). \tag{28}$$

Again, these equations show that an individual with a Kantian moral concern ($\kappa_i > 0$) is not only influenced by his belief about the opponent's strategy, but also by what he would himself do at every decision node of the game tree.

Appendix A3 Copula estimation

We use copula methods to describe the joint parameter distributions for the individual estimates of α_i, β_i and κ_i. For this, let X_α, X_β and X_κ be random variables, possibly statistically dependent, with marginal CDFs F_α, F_β and F_κ. By Sklar's Theorem, their joint CDF can be written in the form

$$F\left(x_\alpha, x_\beta, x_\kappa\right) = C\left(F_\alpha\left(x_\alpha\right), F_\beta\left(x_\beta\right), F_\kappa\left(x_\kappa\right)\right).$$

We follow a two-step approach (Joe & Xu, 1996; Cherubini, Luciano, & Vecchiato, 2004). First, we fit the marginal distributions. For this, we assume that each preference parameter follows a Gumbel distribution, with CDF

$$F\left(x\right) = \exp\left[-e^{-(x-a)/b}\right],$$

where $a \in \mathbb{R}$ is usually called the *location*, and $b > 0$ the *scale*. The associated PDF is

$$f\left(x\right) = \frac{1}{b}\exp\left[-(x-a)/b - e^{-(x-a)/b}\right].$$

The empirical distributions of α_i and κ_i have a relatively long right tail (see Figure 3), which fits well with the Gumbel distribution. The empirical distribution of β_i has a relatively long left tail, therefore, we fit the reverse distribution, i.e. we fit the distribution of $-\beta_i$.

In the second step, we estimate the copula. We assume a Gumbel copula, which has the form:

$$\begin{aligned} C\left(F_\alpha\left(x_\alpha\right), F_{-\beta}\left(x_{-\beta}\right), F_\kappa\left(x_\kappa\right)\right) \;=\; & \\ & \exp\left(-\left[\left(-\ln F_\alpha\left(x_\alpha\right)\right)^\omega + \left(-\ln F_{-\beta}\left(x_{-\beta}\right)\right)^\omega + \left(-\ln F_\kappa\left(x_\kappa\right)\right)^\omega\right]^{1/\omega}\right) \end{aligned}$$

for some $\omega \geq 1$, where $\omega = 1$ represents statistical independence.

In both steps we use maximum likelihood to estimate parameters. Table A.11 shows the estimated parameters, and Figure 3 plots the estimated marginal distributions together with the empirical distributions. For the joint distribution, we estimate $\omega = 1.40$. To put this into perspective, this estimate implies a Kendall's tau of $\tau = 1 - \frac{1}{1.40} = 0.29$. This compares well to the bivariate correlations (see Section 4.1). Expressed in Kendall's tau, the correlation between α_i and $-\beta_i$ is $\tau = 0.18$, for α_i and κ_i we obtain $\tau = 0.33$ and for $-\beta_i$ and κ_i we obtain $\tau = 0.17$.

Table A.11: Individual parameter estimates (all subjects)

Panel A: Marginal distributions	α_i	$-\beta_i$	κ_i
a	0.08	−0.32	0.06
b	0.14	0.33	0.11
Panel B: Joint distribution			
ω	1.40		

Notes: Table based on estimates from our core sample of 112 subjects.

Appendix A4 Robustness

A4.1 Risk aversion

We estimate individual parameters under CRRA preferences as in equations (15) and (16)) by imposing risk parameters r_i based on the lottery choices in the Eckel and Grossman (2002) task. Table A.1 summarizes the lottery choices and implied risk parameters.

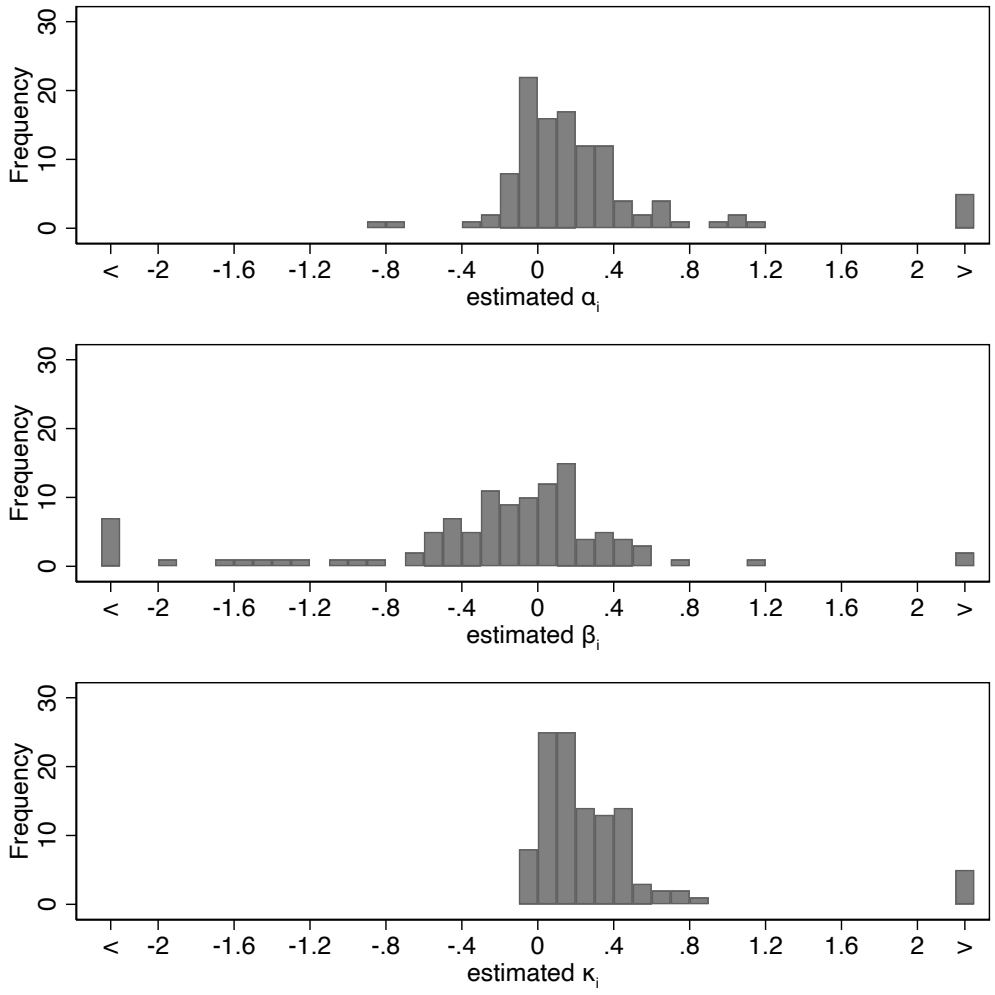
Figure A.4 shows the distributions of the parameter estimates when assuming CRRA preferences. As under risk neutrality, most parameter estimates of α_i (77 out of 112) and κ_i (104 out of 112) are positive (signed-rank tests, $p < 0.001$). While we observed that most estimates of β_i are positive under risk neutrality, we now observe that most estimates of β_i (65 out of 112) are negative under CRRA preferences (signed-rank test, $p = 0.004$).

Figure A.5 shows scatter plots of individual parameter estimates under both assumptions, with estimates under risk neutrality on the horizontal axis and estimates under (individual specific) CRRA preferences on the vertical axis. Each dot represents an individual subject. The diagrams suggest that the risk-neutral and CRRA estimates are strongly correlated. Indeed, for the inequity parameter α_i (when behind) the Spearman rank correlation is $\rho = 0.703$. For the inequity parameter β_i (when ahead) it is $\rho = 0.728$, and for the Kantian morality parameter κ_i it is $\rho = 0.523$ (all three rank correlations hold for $p < 0.001$, $n = 112$).

The middle panel in Figure A.5 also shows that the β_i estimates are much higher under risk neutrality than under CRRA.[33] Indeed, for 97 out of 112 subjects, the risk-neutral

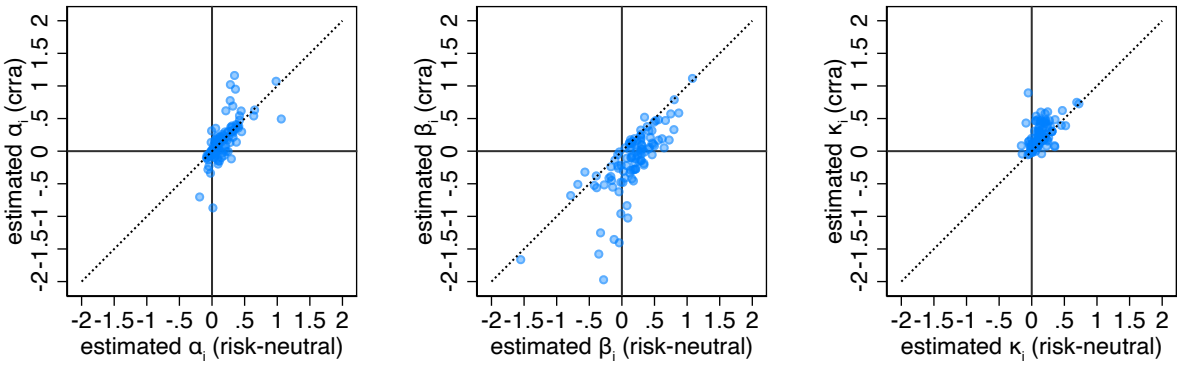
[33] One can easily see how assuming risk neutrality would bias estimates of β_k. Take for example the UG protocol. Both risk aversion and 'aheadness aversion' ($\beta_i > 0$) would induce one to choose E over U. To further see why risk aversion leads to lower degrees of aheadness aversion—sometimes even aheadness loving—and higher degrees of Kantian morality than under risk neutrality, let (for the sake of this argument) $u(m)$ denote the material utility associated with the monetary payoff m. If sufficiently strong, both aheadness aversion and Kantian morality can make an individual refrain from defecting in the Sequential Prisoner's Dilemma, keeping the money in the Trust game, and proposing the unequal split in the Ultimatum game. However, the effect appears for different reasons: while aheadness aversion entails disutility proportional to the difference $u(T) - u(S)$, Kantian morality generates utility proportional to $u(T) + u(S)$. Since $u(T) - u(S)$ relative to $u(T) + u(S)$ is smaller for a strictly concave function u than for a linear one, the

Figure A.4: Distributions of individual parameter estimates (allowing for risk aversion)



Note: All estimates of α_i, β_i and κ_i larger than 2 in absolute value are grouped in bins ("<" and ">") at the extremes of the horizontal axis. Figure based on all our 'core' sample of 112 subjects. For all subjects, we use the lottery choices to impose risk attitudes.

Figure A.5: Correlations between risk-neutral and CRRA estimates



Notes: Figures shows estimates smaller than 2 in absolute value. Dotted lines indicate 45 degree lines. Figure based on our 'core sample' of 112 subjects.

estimate is higher than the CRRA estimate (signed-rank test, $p < 0.001$). By contrast, the risk-neutral estimates of κ_i (87 out of 112, signed-rank test: $p < 0.001$) are lower for most subjects than under CRRA. For α_i there is no clear directional shift as the risk-neutral estimates are higher than the CRRA estimates for 51 out of 112 subjects (signed-rank test: $p = 0.857$). For the majority of subjects (68 out of 112), assuming CRRA preferences instead of risk neutrality leads to a higher log-likelihood, indeed indicating a better fit under CRRA preferences.

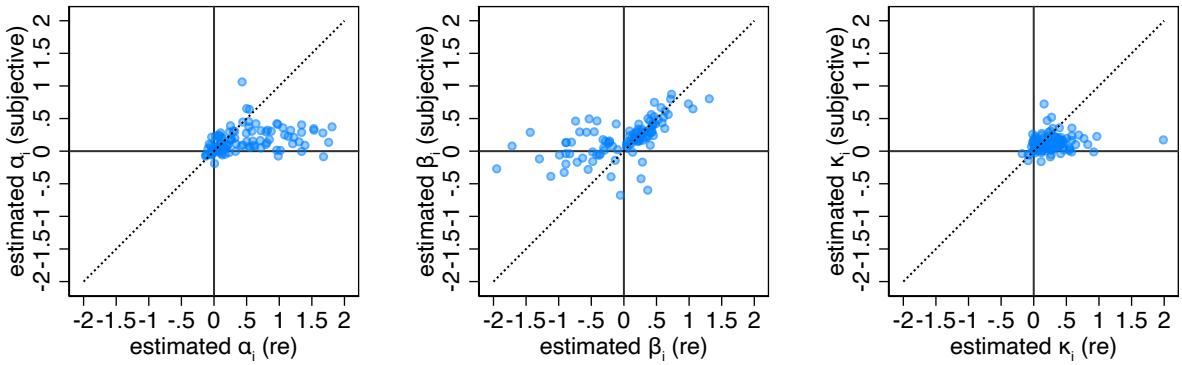
Table 5 in the main text presents the estimates of the finite mixture estimation under CRRA preferences (we impose logarithmic utility ($r_k = 1$) for all types). For a discussion, see section 5.1 in the main text.

A4.2 Rational expectations

In the main analyses, we assume that subjects maximize their expected utility given their stated beliefs. As a robustness check, we also estimate preference parameters under the alternative assumption of rational expectations. Figure A.6 shows correlations between the individual estimates using subjective and rational expectations. For all three pref-

above mentioned pro-social actions will appear to be driven more by Kantian morality than by aheadness aversion for a strictly concave function u than for a linear one.

Figure A.6: Correlations between estimates using subjective and rational expectations



Notes: Figures shows estimates smaller than 2 in absolute value. Dotted lines indicate 45 degree lines. Figure based on our 'core sample' of 112 subjects.

erence parameters, the estimates under the two assumptions are positively correlated. For the inequity parameter α_i (when behind) the Spearman rank correlation is $\rho = 0.403$ ($p < 0.001$, $n = 112$). For the inequity parameter β_i (when ahead) it is $\rho = 0.706$ ($p < 0.001$, $n = 112$), and for the Kantian morality parameter κ_i it is $\rho = 0.219$ ($p = 0.020$, $n = 112$).

Table A.12 shows the finite mixture estimates when we assume rational expectations. The representative agent with rational expectations is characterized by a combination of behindness aversion ($\alpha_k > 0, \beta_k = 0$) and morality ($\kappa_k > 0$). Compared to the model with subjective expectations (see Table 4 in the main text), the estimates for α_k and κ_k are larger when we assume rational expectations. The estimate for β_k is zero when we assume rational expectations, where it was positive under subjective expectations. For the representative agent model, the log-likelihood is lower when assuming rational expectations. For the two-types model and three-types model, assuming rational expectations leads to qualitatively similar results as under subjective expectations for some types, but quite different estimates for other types. For the two-types model, Type 1 again displays a combination of inequity aversion and morality, with estimates very close in magnitude to those under subjective expectations. Assuming rational expectations, Type 2 now combines strong spite ($\alpha_k > 0, \beta_k < 0$) with strong morality ($\kappa_k > 0$). This contrasts with the estimates under subjective expectations where Type 2 combined behindness aversion

Table A.12: Estimates at the aggregate level (assuming rational expectations)

	1 type	2 types		3 types		
	Rep. agent	Type 1	Type 2	Type 1	Type 2	Type 3
α_k	0.41	0.12	1.02	0.16	0.08	1.05
	(0.05)	(0.02)	(0.09)	(0.07)	(0.05)	(0.09)
β_k	0.00	0.35	−0.65	0.28	0.41	−0.69
	(0.07)	(0.03)	(0.12)	(0.05)	(0.10)	(0.16)
κ_k	0.27	0.14	0.49	0.09	0.24	0.51
	(0.03)	(0.03)	(0.05)	(0.03)	(0.06)	(0.06)
λ_k	10.67	7.84	10.35	8.14	6.07	10.11
	(0.62)	(0.57)	(1.00)	(0.77)	(0.90)	(0.88)
ϕ_k	1.00	0.56	0.44	0.37	0.22	0.42
	(-)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
$\ln L$	-2689.8	-2316.0			-2261.9	
$EN(\boldsymbol{\tau})$	0.00	2.09			9.97	
ICL	5398.6	4676.5			4599.8	
NEC	-	0.006			0.023	

Notes: Bootstrapped standard errors in parentheses. Table based on our 'core sample' of 112 subjects. For all types, we assume risk neutrality ($r_k = 0$) and rational expectations.

with milder morality.[34] For the three-types model, Types 1 and 2 are again very similar under both subjective and rational expectations, while Type 3's estimates are quite different. Given a number of types, the ICL scores under rational expectations are higher than under subjective expectations, indicating a worse fit under rational expectations. In sum, most estimated preference parameters for the multi-type models are very similar under both assumptions, while for some types the estimates differ. In combination with the higher ICL scores under rational expectations, this suggests that assuming subjective expectations is an important assumption for part of the population.

A4.3 Game protocol type specific noise parameters

In Table A.13 we present estimates of finite mixture models where we allow for different noise parameters λ for each game protocol type (SPD, TG, UG). Comparing the estimates

[34] Table A.6 (panels D and E) shows that the assignment of subjects to types is similar under subjective and rational expectations.

Table A.13: Estimates at the aggregate level (game protocol type specific noise parameters)

	1 type	2 types		3 types		
	Rep. agent	Type 1	Type 2	Type 1	Type 2	Type 3
α_k	0.15	0.11	0.15	0.19	0.10	0.08
	(0.01)	(0.02)	(0.03)	(0.03)	(0.02)	(0.04)
β_k	0.26	0.40	−0.02	0.08	0.42	−0.02
	(0.03)	(0.03)	(0.04)	(0.04)	(0.03)	(0.09)
κ_k	0.09	0.08	0.09	0.10	0.08	0.07
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)
$\lambda_{SPD,k}$	6.46	8.23	2.92	4.78	8.63	0.31
	(0.45)	(0.84)	(0.38)	(0.94)	(0.43)	(0.10)
$\lambda_{TG,k}$	10.25	12.94	3.56	3.80	12.05	4.35
	(1.39)	(2.41)	(0.70)	(0.94)	(0.60)	(0.96)
$\lambda_{UG,k}$	5.83	4.55	6.19	5.86	4.29	6.73
	(0.49)	(0.56)	(0.67)	(0.94)	(0.31)	(0.54)
ϕ_k	1.00	0.59	0.41	0.28	0.52	0.20
	(-)	(0.05)	(0.05)	(0.07)	(0.05)	(0.04)
$\ln L$	-2418.8	-2203.9			-2184.2	
$EN(\boldsymbol{\tau})$	0.00	4.13			14.56	
ICL	4866.0	4473.4			4477.3	
NEC	-	0.019			0.062	

Notes: Bootstrapped standard errors in parentheses. Table based on our 'core sample' of 112 subjects.

in Table A.13 to those with a single λ for each type in Table 4, we find that the estimates of the preference parameters are nearly identical for the 1-type and 2-types models. For the 3-types models, the point estimates differ somewhat, but the three types are qualitatively similar. In both cases, Type 1 displays a combination of inequity aversion and Kantian morality. Type 2 combines aheadness aversion with Kantian morality in both cases, although this type is also motivated by behindness aversion in Table A.13, where in Table 4 the α estimate was very close to zero. Type 3 combines aheadness aversion with a Kantian moral concern in both cases.

Appendix A5 Simulations

In the process of selecting game protocols for the experiment, we conducted some simulations to check whether we can retrieve the original parameters based on the set of experimental game protocols. In this appendix, we describe how such simulations were conducted.

Generating simulated data

First, for each (simulated) subject i, we randomly draw preference parameters $\alpha_i, \beta_i, \kappa_i$ independently from uniform distributions. For α_i and β_i, we draw the preference parameters from $U[-0.5, 0.5]$, while we draw κ_i from $U[0, 0.5]$. In the simulations, we set $\delta_i = 0$. Second, for each subject i and game protocol g we compute the expected utility for each possible pure strategy x_i based on utility function (1), with subjective beliefs $\hat{y}_i$ drawn independently from $U[0, 1]$. We then compute choice probabilities for each pure strategy x_i based on equation (8), where for all subjects we impose some fixed noise parameter λ_i. Based on these choice probabilities, we randomly select a behavioral strategy for each subject i and each game protocol g.

Estimation

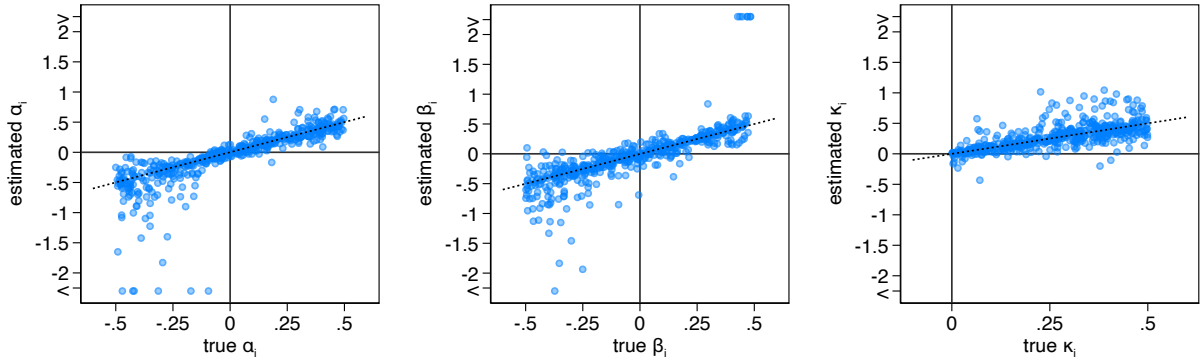
For the simulated data, we then estimate individual preference parameters as described in section 3.

Results

Figure A.7 shows the correlations between the simulated ('true') parameters and the estimated parameters, for 500 individuals with relatively low noise levels ($\lambda_i = 0.5$). Most estimated preference parameters lie very close to the 45-degree line, indicating that we can well retrieve the preference parameters.

Figures A.8 and A.9 show simulations with higher noise levels. When increasing the

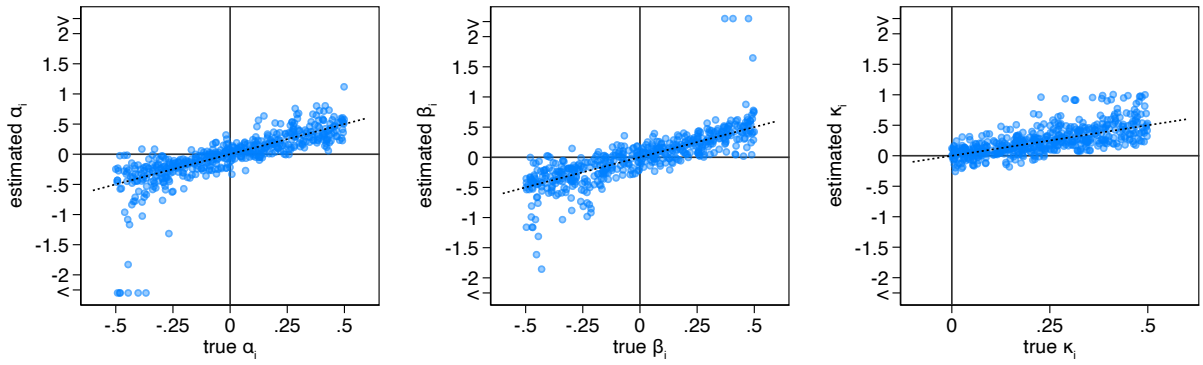
Figure A.7: Simulations ($\lambda_i = 0.5$)



Notes: Scatter plots shows the correlations between the simulated ('true') parameters and the estimated parameters. All estimated parameters larger then 2 in absolute value are grouped in the bins at the extremes of the vertical axes. Dotted lines indicate 45 degree lines. Figure based on 500 simulated subjects.

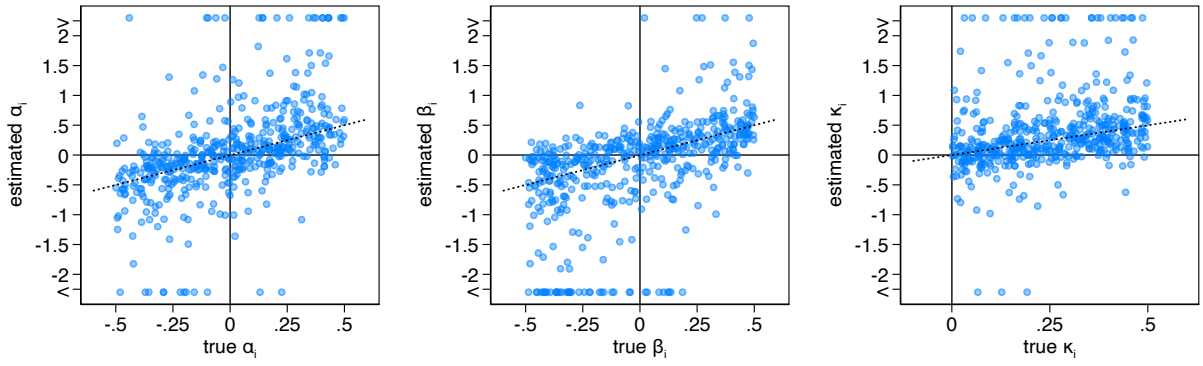
noise parameter to $\lambda_i = 5$, most estimated preference parameters are still close to the 45 degree line (see Figure A.8). Note that this noise level is roughly in the same ballpark as what we estimate in our pre-registered analyses (for the core sample, the median estimated $\lambda_i = 4.5$). When we further increase the noise parameter to $\lambda_i = 20$, estimated preference parameters lie much further from the 45-degree line, but we still observe strong correlations between the true and estimated parameters.

Figure A.8: Simulations ($\lambda_i = 5$)



Notes: Scatter plots shows the correlations between the simulated ('true') parameters and the estimated parameters. All estimated parameters larger then 2 in absolute value are grouped in the bins at the extremes of the vertical axes. Dotted lines indicate 45 degree lines. Figure based on 500 simulated subjects.

Figure A.9: Simulations ($\lambda_i = 20$)



Notes: Scatter plots shows the correlations between the simulated ('true') parameters and the estimated parameters. All estimated parameters larger then 2 in absolute value are grouped in the bins at the extremes of the vertical axes. Dotted lines indicate 45 degree lines. Figure based on 500 simulated subjects.

Appendix A6 Pre-registration

We pre-registered our main design elements (sample size, type of game protocols), and main analyses on aspredicted,org (see XX link). Below we reproduce the pre-registration.

1) Have any data been collected for this study already?
No, no data have been collected for this study yet

2) What's the main question being asked or hypothesis being tested in this study?
We test whether people's preferences in social dilemma situations (SPDs, TGs, UGs) can be well described by 'homo moralis' preferences as in Alger and Weibull (2013).

3) Describe the key dependent variable(s) specifying how they will be measured.
We measure actions and beliefs in SPDs TGs and UGs

4) How many and which conditions will participants be assigned to?
There is one condition (each participant plays the same games, in different, random order, for each session).

5) Specify exactly which analyses you will conduct to examine the main question/hypothesis.
We will use maximum likelihood to estimate (individual) parameters of a utility function that includes three parameters, alpha, beta and gamma. Alpha en beta capture inequity aversion and gamma captures moral preferences. We use a logit specification. Using this model, we compare the predictive value (within the sample) of the general model to restricted versions of the model. The general model nests inequity aversion, altruism, homo moralis and selfish preferences.

6) Any secondary analyses?

7) How many observations will be collected or what will determine sample size? No need to justify decision, but be precise about exactly how the number will be determined. We will run 8 sessions, with 22 people invited for each session. If we have fewer than 120 subjects after the 8 sessions, we will run more sessions until we pass the 120 subjects minimum.

8) Anything else you would like to pre-register?
(e.g., data exclusions, variables collected for exploratory purposes, unusual analyses planned?)

Appendix A7 Experimental instructions

Welcome

Welcome to this experiment. All subjects receive the same instructions. Please read them carefully.

Do not communicate with any of the other subjects during the entire experiment. If you have any questions, raise your hand and wait until one of us comes to you to answer your question in private.

During the experiment you will receive points. These points are worth money. How many points (and hence how much money) you get depends on your own decisions, the decisions of others, and chance. At the end of the experiment the points that you got will be converted to euros and the amount will be paid to you privately, in cash.

Every point is equivalent to 0.17 euro.

Your decisions are anonymous. They will not be linked to your name in any way. Other subjects can never trace your decisions back to you.

Today's experiment consists of two parts. At the beginning of each part, you will receive new instructions. Your decisions made in one part will never affect outcomes in another part, so you can treat both parts as independent.

Decision situations I

In this part, you will participate in 18 different decision situations. For each decision situation, you will be randomly paired with someone else in the lab. Therefore, in each decision situation you will (most likely) be paired with a different subject than in the previous situation. You will never learn with whom you are paired.

The 18 decision situations will all be different, but they all involve two persons, and in all the decision situations one person is assigned to Role A (person A) while the other is assigned to Role B (person B). There are then two kinds of situations, as depicted in Figures 1 (below) and Figure 2 (on the next page).

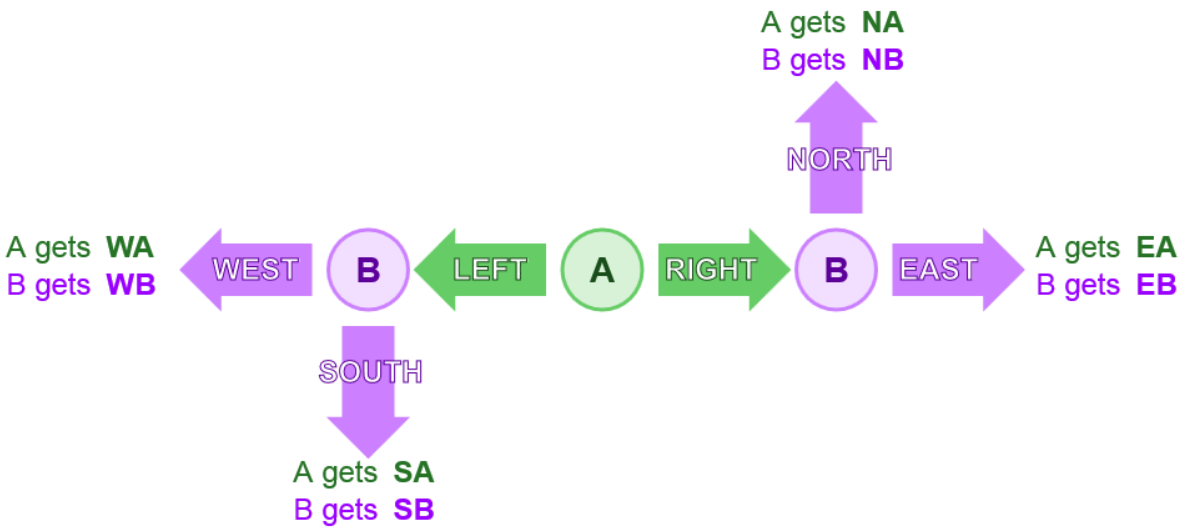
In the situation shown in Figure 1, person A first chooses LEFT or RIGHT. If A chooses LEFT, person B has to choose between WEST or SOUTH. If person A chooses RIGHT, person B has to choose between NORTH and EAST.

The choices of A and B jointly determine the number of points for A and B as follows:

- If A chooses LEFT and B chooses WEST, A gets WA points and B gets WB points
- If A chooses LEFT and B chooses SOUTH, A gets SA points and B gets SB points
- If A chooses RIGHT and B chooses NORTH, A gets NA points and B gets NB points
- If A chooses RIGHT and B chooses EAST, A gets EA points and B gets EB points

The values of WA, WB, SA, SB, NA, NB, EA and EB vary from one decision situation to another. At the beginning of each decision situation, you and all others in the lab will be informed of the values.

Figure 1



Decision situations II

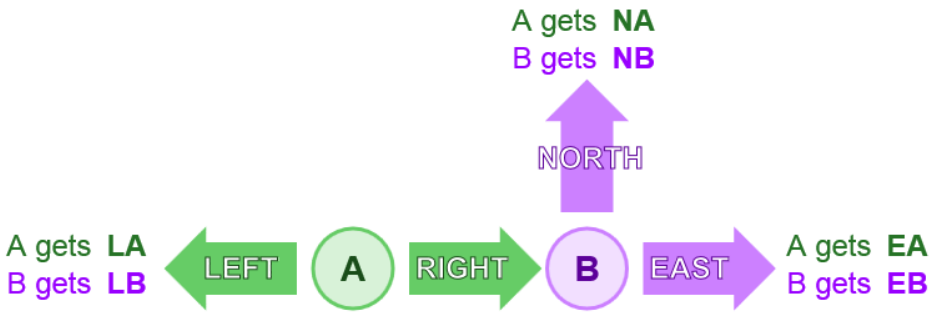
In the decision situation shown in Figure 2, person A first chooses LEFT or RIGHT. If A chooses LEFT, person B has no choice to make. If A chooses RIGHT, B has to choose between NORTH and EAST.

The choices of A and B jointly determine the number of points for A and B as follows:

- If A chooses LEFT, A gets LA points and B gets LB points
- If A chooses RIGHT and B chooses NORTH, A gets NA points and B gets NB points
- If A chooses RIGHT and B chooses EAST, A gets EA points and B gets EB points

The values of LA, LB, NA, NB, EA and EB vary from one decision situation to another. At the beginning of each decision situation, you and all others in the lab will be informed of the values.

Figure 2



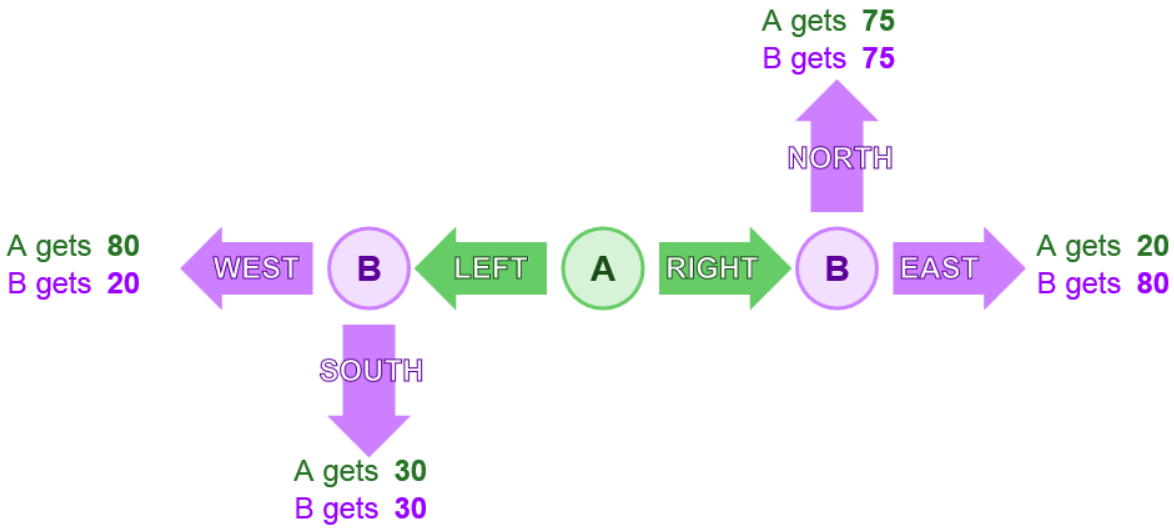
Example

The figure below gives an example of a decision situation. This decision situation is randomly selected. Remember that each of the 18 decision situations will be different.

In this example:

- If A chooses LEFT and B chooses WEST, A gets 80 points and B gets 20 points
- If A chooses LEFT and B chooses SOUTH, A gets 30 points and B gets 30 points
- If A chooses RIGHT and B chooses NORTH, A gets 75 points and B gets 75 points
- If A chooses RIGHT and B chooses EAST, A gets 20 points and B gets 80 points

If you want to see another example, click here



Decisions and payments

You will see 18 different decision situations. For each decision situation, you will be asked two things.

First, we will ask you what you want to do in Role A and what you want to do in Role B.

Second, we will ask you to guess what the others in the lab will do in Role A and what they will do in Role B. Specifically, we will ask you to guess:

- What percentage of the other people in the lab choose LEFT and what percentage choose RIGHT when in Role A
- What percentage of the other people in the lab choose WEST and what percentage choose SOUTH when facing that choice in Role B
- What percentage of the other people in the lab choose NORTH and what percentage choose EAST when facing that choice in Role B.

Both your decisions and your guesses will determine how many euros you get at the end of the experiment. Specifically, at the end of today's experiment, **two of the 18 decision situations will be randomly selected for payment: for one of these situations you**

get points from the decisions, while for the other situation you get points from your guesses. The same two decision situations will be selected for everyone in the lab.

Your decisions

For one decision situation you and the others in the lab get points from the decisions. For this situation, either you or the person you are paired with is assigned to Role A, while the other is assigned to Role B, with equal probability for each case. The number of points you and this other person get is then determined by your decision in the role to which you were assigned and the decision of the other person in the role to which (s)he was assigned.

Note that it is equally likely that your choices in role A or role B count. Think about flipping a coin: if heads comes up you will be in role A and if tails comes up you will be in role B. When you make your decisions, you do not know which role you have and you should therefore make decisions as if each role could determine the outcome, which is the case.

Your guesses

For another decision situation you and the others in the lab get points from the guesses. You get more points the closer your guesses are to what the others actually choose in both roles A and B. One of the guesses that you make in this situation will be randomly selected for payment. Specifically, you get between 0 and 50 points depending on the accuracy of your guess. If you want to earn as much as possible with your guesses, you should simply answer with what you really think is the most likely answer to each question. Your guesses do not have any impact on the number of points that the others in the lab get.

If you want to see how your earnings are calculated you can click here.

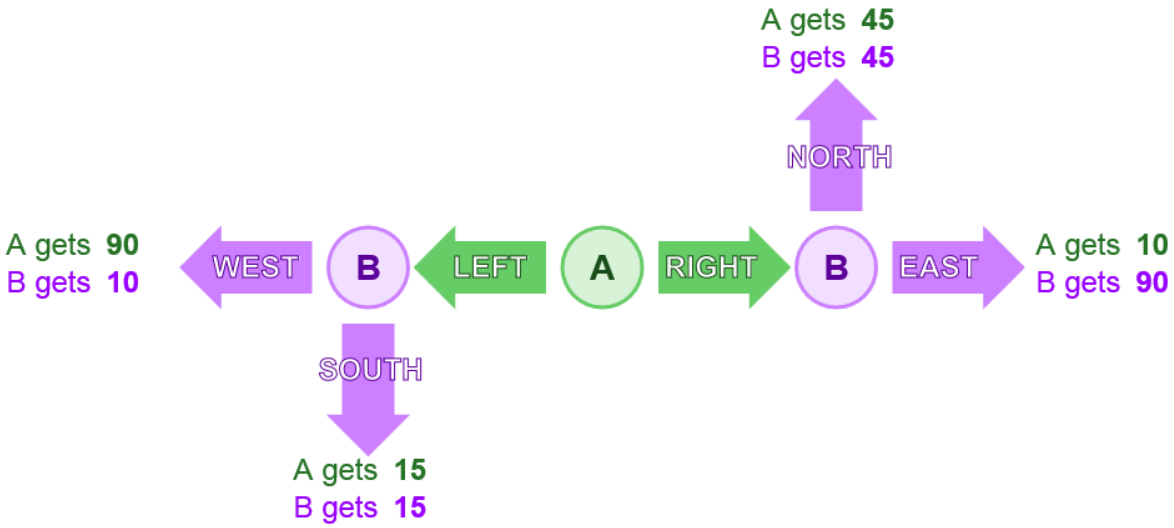
Decision screens

Below you can see and try the decision screens. First, you will see the screen where you will be asked for a decision in a decision situation. If you make a decision, you will be taken to the screen where you will be asked for a guess about what others will do.

In the examples below, all decision situations are chosen randomly. You can try the decision screens as often as you want.

Show example

Quiz questions I



Please answer the following quiz questions. If you have any questions please raise your hand.

The 18 decision situations:

O are always the same

O are sometimes the same

O are always different

The figure shows a possible decision situation. The figure merely serves as an example, the decision situation has been selected randomly.

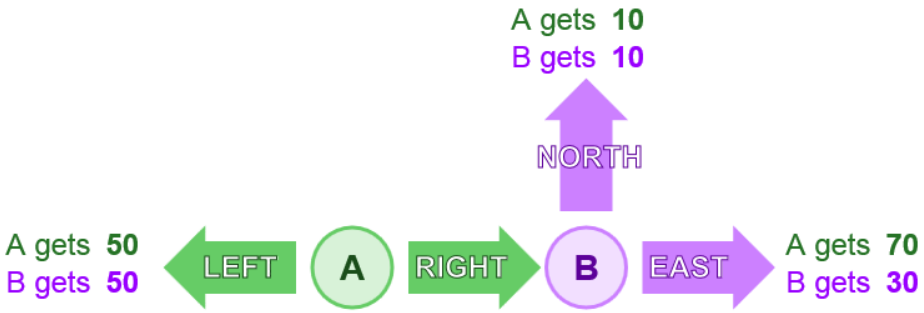
Suppose A chooses LEFT and B chooses SOUTH and EAST. How much would A and B earn?

A would earn: ___ points B would earn: ___ points

Suppose A chooses RIGHT and B chooses WEST and NORTH. How much would A and B earn?

A would earn: ___ points B would earn: ___ points

Quiz questions II



Please answer the following quiz questions. If you have any questions please raise your hand.

In each decision situation:

O you will have the same role (A or B)

O it is equally likely that you will be in role A or B

In each decision situation:

O you will be paired with the same subject

O you will be paired with a randomly determined subject

The figure shows a possible decision situation. The figure merely serves as an example, the decision situation has been selected randomly.

Suppose A chooses LEFT and B chooses NORTH. How much would A earn?

A would earn: ___ points B would earn: ___ points

Suppose A chooses RIGHT and B chooses EAST. How much would B earn?

A would earn: ___ points B would earn: ___ points

End of instructions

You have reached the end of the instructions. You can still go back by using the menu above. If you are ready, click on 'continue' below. If you need help, please raise your hand.

As soon as everyone has finished with instructions the experiment will start. During the experiment, you can take as much time as you need for each decision situation.

Part II

In this part you choose one of the six options listed below. You choose by clicking on the option you prefer. Each option has two possible outcomes (Outcome A or Outcome

B) that are equally likely to occur. Think about the flip of a coin: heads (Outcome A) and tails (Outcome B) are equally likely.

At the end of the experiment, the computer will randomly select Outcome A or Outcome B. You will receive the number of points corresponding to the option you chose. For example: If you choose option 4 you will receive 30 points if Outcome A is selected by the computer and 9 points if Outcome B is selected by the computer.